Enhancing the Treatment of Systems Integration in Long-term Energy Models

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Abstract

Securing access to affordable energy services is of central importance to our societies. To do this sustainably, energy systems design should be – amongst other things – environmentally compliant and reconcile with the integrated management of potentially limiting resources.

This work considers the role for so-called 'Smart Grids' to improve the delivery of energy services. It deals with the integration of renewable energy technologies to mitigate climate change. It further demonstrates an approach to harmonise potentially conflicting energy, water and land-use strategies. Each presents particular challenges to energy systems analysis.

Computer aided models can help identify energy systems that most effectively meet the multiple demands placed on them. As models constitute a simple abstraction of reality, it is important to ensure that those dynamics that considerably impact results are suitably integrated. In its three parts, this thesis extends long-term energy system models to consider improved integration between: (A) supply and demand through Smart Grids; (B) timeframes by incorporating short-term operating constraints into long-term models; and (C) resource systems by linking multiple modelling tools.

In Part A, the thesis explores the potential of Smart Grids to accelerate and improve electrification efforts in developing countries. Further, a long-term energy system model is enhanced to investigate the Smart Grid benefits associated with a closer integration of supply, storage and demand-side options. In Part B, the same model is extended to integrate flexibility requirements. The benefits of this integration are illustrated on an Irish case study on high levels of wind power penetrations. In Part C, an energy model is calibrated to consider climate change scenarios and linkages with land-use and water models. This serves to assess the implications of introducing biofuels on the small island developing state of Mauritius.

The thesis demonstrates that too weak integration between models and resource systems can produce significantly diverging results. The system configurations derived may consequently generate different – and potentially erroneous – policy and investment insights.

Keywords: Power system models; Energy system models; Resource system models; Smart Grids; Operating reserve; Biofuels; Sub-Saharan Africa; Ireland; Mauritius;

Sammanfattning

Säker och prisvärd tillgång till energitjänster är en central fråga för dagens samhällen. För att tillgodose samhällen med hållbara energitjänster bör energisystemen designas för att – bland annat – möta de miljömässiga kraven samt hantera potentiellt begränsade resurser. Den här avhandlingen undersöker de ”smarta” elnätens roll för bättre tillhandahållande av energitjänster. Avhandlingen behandlar integration av förnybar energiteknik för minskad klimatpåverkan samt demonstrerar ett tillvägagångssätt för att förena potentiellt motstridiga energi-, vatten- och markanvändningsstrategier. Dessa uppvisar särskilda utmaningar i energisystemanalyser.

Datorstödda modeller kan användas för att identifiera energisystem som på effektivast sätt möter samhällets krav. Datorstödda modeller är, per definition, förenklingar av verkligheten och det är därför viktigt att säkerställa en korrekt representation av det verkliga systemets dynamik. Den här avhandlingen förstärker energisystemmodeller för långsiktsprognoser utifrån tre aspekter: förbättra integrationen av (A) tillgång och efterfrågan genom smarta elnät; (B) olika tidsaspekter genom att inkludera kortsiktiga operativa begränsningar; samt (C) resurssystem genom att sammanlänka olika modelleringsverktyg.

I del A utforskades de smarta elnätens potential för att förbättra elektriska system i utvecklingsländer. En befintlig energisystemmodell förstärktes för att behandla smarta elnät och kan därmed fånga fördelarna förknippade med energilagring och energianvändning. I del B utvidgades en energisystemmodell för långsiktsprognoser med flexibilitet för kortsiktiga operativa begränsningar. En fallstudie fokuserad på ett vindkraftsdominerat irländskt elnät genomfördes för att demonstrera fördelarna av modellutvecklingen. I del C kalibrerades en energisystemmodell för att ta klimatscenarier i beaktande samt energisystemets kopplingar till markanvändning och vattenresurssystem. En fallstudie fokuserad på Mauritius energisystem genomfördes för att undersöka konsekvenserna av en potentiell introducering av biobränslen.

Avhandlingen demonstrerar att undermålig integration av energimodeller och resurssystem kan leda till avsevärda avvikelser i resultaten. Slutsatser som dras utifrån dessa resultat kan därmed leda till vitt skilda – och potentiellt felaktiga – underlag för investeringar och energipolitiska rekommendationer.

Nyckelord: kraftsystemmodeller; energisystemmodeller; resursmodeller; smarta elnät; operativ reservkapacitet; biobränslen; Afrika söder om Sahara; Irland; Mauritius;

Publications

This doctoral thesis is based on the publications listed below. All underlying energy related analysis and energy model development[1] was performed by the author of this thesis.

I. **Welsch, M.,** Bazilian, M., Howells, M., Divan, D., Elzinga, D., Strbac, G., Jones, L., Keane, A., Gielen, D., Balijepalli, V.S.K.M., Brew-Hammond, A., Yumkella, K., Smart and Just Grids for sub-Saharan Africa: Exploring options, Renewable and Sustainable Energy Reviews 20, pp. 336–352, 2013.

II.a. **Welsch, M.,** Howells, M., Bazilian, M., DeCarolis, J., Hermann, S., Rogner, H.H., Modelling Elements of Smart Grids – Enhancing the OSeMOSYS (Open Source Energy Modelling System) code. Energy 46 (1), pp. 337–350, 2012.

II.b. **Welsch, M.,** Howells, M., Bazilian, M., DeCarolis, J., Hermann, S., Rogner, H.H., Supplement to: Modelling Elements of Smart Grids – Enhancing the OSeMOSYS Code (DESA/12/2), Working Paper Series. KTH Royal Institute of Technology, Stockholm, 2012.

III. **Welsch, M.,** Howells, M., Hesamzadeh, M., Ó Gallachóir, B., Deane, J.P., Strachan, N., Bazilian, M., Kammen, D.M., Jones, L., Rogner, H.H., Strbac, G., Supporting Security and Adequacy in Future Energy Systems – The need to enhance long-term energy system models to better treat issues related to variability, revisions submitted.

IV. **Welsch, M.,** Deane, J.P., Howells, M., Rogan, F., Ó Gallachóir, B., Rogner, H.H., Bazilian, M., Incorporating Flexibility Requirements into Long-term Models – A Case Study on High Levels of Renewable Electricity Penetration in Ireland, submitted.

V. Howells, M., Hermann, S., **Welsch, M.,** Bazilian, M., Segerström, R., Alfstad, T., Gielen, D., Rogner, H., Fischer, G., van Velthuizen, H., Wiberg, D., Young, C., Röhrl, R.A., Mueller, A., Steduto, P., Ramma, I., Integrated analysis of climate change, land-use, energy and water strategies, Nature Climate Change 3 (7), pp. 621–626, 2013.

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1 In this context, the term ‘development’ either refers to the calibration of an existing modelling framework or model code extensions to account for previously ignored dynamics.

VI. **Welsch, M.,** Hermann, S., Howells, M., Rogner, H.H., Young, C., Ramma, I., Bazilian, M., Fischer, G., Alfstad, T., Gielen, D., Le Blanc, D., Röhrl, A., Steduto, P., Müller, A., Adding Value with CLEWS – Modelling the Energy System and its Interdependencies for Mauritius. Applied Energy 113, pp. 1434–1445, 2014.

Papers I – VI and Paper VI were directly integrated into the three main parts of this thesis, apart from some expansions and adjustments to improve readability. Part A focuses on integration between technologies and draws on Paper I for Section 1 and Paper II.a and II.b for Section 2. Papers III and IV were restructured and merged within Part B, which focuses on integration between timeframes. Part C focuses on integration between resource systems. The findings of Paper V were summarised in Section 1 of Part C, which otherwise draws on Paper VI.

Other journal papers, book chapters and contracted work by the author which served to inform this thesis include:

1. **Welsch, M.,** Perspectives for the Development of Smart Grids for Developing Countries (DCs) and Emerging Markets (EMs) – Discussion Paper, in: GIZ Visionary Workshop. Berlin, Germany, 2011.
2. **Welsch, M.,** Mentis, D., Howells, M., Long Term Energy Systems Planning: Accounting for Short Term Variability and Flexibility, Book Chapter in: Renewable Energy Integration: Practical Management of Variability, Uncertainty and Flexibility in Power Grids, Elsevier, submitted.
3. Hermann, S., **Welsch, M.,** Segerströn, R.E., Howells, M.I., Young, C., Alfstad, T., Rogner, H.-H., Steduto, P., Climate, land, energy and water (CLEW) interlinkages in Burkina Faso: An analysis of agricultural intensification and bioenergy production, Natural Resources Forum 36, 245–262, 2012.
4. Rogan, F., Cahill, C.J., Daly, H.E., Dineen, D., Deane, J.P., Heaps, C., **Welsch, M.,** Howells, M., Bazilian, M., Ó Gallachóir, B., LEAPs and Bound – An Energy Demand and Constraint Optimized Model of the Irish Energy System, Energy Efficiency, 2013.
5. Bazilian, M., Miller, M., Detchon, R., Liebreich, M., Blyth, W., Futch, M., Modi, V., Jones, L., Barkett, B., Howells, M., MacGill, I., Kammen, D.M., Mai, T., Wittenstein, M., Aggarwal, S., O'Malley, M., Carvallo, J.P., **Welsch, M.,** Pugh, G., Weston, R., Arent, D.J., Accelerating the

Global Transformation to 21st Century Power Systems, The Electricity Journal 26, 39–51, 2013.

6. Taliotis, C., Miketa, A., Howells, M., Hermann, S., **Welsch, M.,** Broad, O., Rogner, H., Bazilian, M., Gielen, D., An indicative assessment of investment opportunities in the African electricity supply sector, submitted.

7. Taliotis, C., Bazilian, M., **Welsch, M.,** Gielen, D., Howells, M., Grand Inga to power Africa: Scenarios to 2035, submitted.

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Most of all I would like to thank my family, and especially my parents who gave me the opportunity to freely decide on my educational career. It is just so much easier to try out new things and explore new places in the world knowing there is always a stable base back home to which I can return and recover from any struggles.

Nomenclature

Abbreviations

a	Annum
AC	Alternating Current
AEZ	Agro-Ecological Zones
AGECC	The UN Secretary General's Advisory Group on Energy and Climate Change
AIMMS	Advanced Interactive Multidimensional Modeling System
AMI	Advanced Metering Infrastructure
AMMO	ActiveX Mathematical Modeling Objects
AMPL	A Mathematical Programming Language
BAU	Business As Usual
BPL	Broadband over Power Line
CAES	Compressed Air Energy Storage
CAPP	Central African Power Pool
CC	Combined cycle
CCS	Carbon Capture and Storage
CEMAC	Economic and Monetary Community of Central Africa
CES	Constant Elasticity of Substitution
CGE	Computable General Equilibrium
COMESA	Common Market for Eastern and Southern Africa
COPT	Capacity Outage Probability Table
CPLEX	IBM ILOG CPLEX Optimization Studio
CPU	Central Processing Unit
CUE	Cost Of Unserved Energy
DC	Direct Current
dena	Deutsche Energie-Agentur
DOE	U.S. Department of Energy
DSM	Demand Side Management
EAC	East African Community
EAPP	East African Power Pool

EC	European Commission
ECOWAS	Economic Community of West African States
EEG	Erneuerbare Energien Gesetz
EMCAS	Electricity Market Complex Adaptive System
ENTSO-E	European Network of Transmission System Operators for Electricity
EPRI	Electric Power Research Institute
ETP	European Technology Platform
ETS	EU Emissions Trading System
ETSAP	Energy Technology Systems Analysis Program
EU	European Union
EUR	Euro
FEMA	Forum of Energy Ministers of Africa
GAMS	General Algebraic Modeling System
GCM	General Circulation Models
GDP	Gross Domestic Product
GEA	Global Energy Assessment
GHG	Greenhouse Gas
GIS	Geographic Information System
GLPK	GNU Linear Programming Kit
GWh	Gigawatt Hour
GWa	Gigawatt Year
HOMER	Hybrid Optimization Model for Electric Renewables
HV	High Voltage
HVDC	High Voltage Direct Current
IAEA	International Atomic Energy Agency
IIASA	International Institute for Applied Systems Analysis
ICT	Information and Communication Technology
IEA	International Energy Agency
IGCC	Integrated Gasification Combined Cycle
IPCC	Intergovernmental Panel on Climate Change
IRP	Integrated Resource Planning
KTH	Kungliga Tekniska Högskolan
ktoe	Kilotonne of Oil Equivalent

kWh	Kilowatt Hour
LEAP	Long-range Energy Alternatives Planning System
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
MAED	Model for Analysis of Energy Demand
MATLAB	Matrix Laboratory
MESSAGE	Model of Energy Supply Strategy Alternatives and their General Environmental Impacts
MDG	Millennium Development Goal
MPS	Mathematical Programming System
MTTR	Mean Time To Repair
MW	Megawatt
MWh	Megawatt Hour
NEA	Nuclear Energy Agency
NETL	National Energy Technology Laboratory
NREL	National Renewable Energy Laboratory
OCGT	Open Cycle Gas Turbine
OECD	Organisation for Economic Co-operation and Development
OSeMOSYS	Open Source Energy Modelling System
PSI	Paul Scherrer Institute
PV	Photovoltaic
RAM	Random Access Memory
ReEDS	Regional Energy Deployment System
RISDP	Regional Indicative Strategic Development Plan
SADC	Southern African Development Community
SAPP	South African Power Pool
SCADA	Supervisory Control and Data Acquisition
SEI	Stockholm Environment Institute
SIDS	Small Island Developing State
TED	Technology and Environmental Database
TIMES	The Integrated MARKAL-EFOM System
TJ	Terajoule
TSO	Transmission System Operator
UCC	University College Cork

UCL	University College London
UCT	University of Cape Town
UK	United Kingdom
UKERC	UK Energy Research Centre
UN	United Nations
UNEP	United Nations Environment Programme
UNIDO	United Nations Industrial Development Organisation
UPFC	Unified Power Flow Controller
U.S.	United States of America
USD	U.S. Dollar
VoLL	Value of Lost Load
V2G	Vehicle-to-Grid
WAPP	West African Power Pool
WASP	Wien Automatic System Planning Programme
WEAP	Water Evaluation and Planning System
WEC	World Energy Council
WEM	World Energy Model
WTO	World Trade Organization

Indices and Parameters

To improve readability, indices and parameters of any model enhancements are defined before presenting their algebraic formulations.

Table of Contents

Introduction

This introduction presents energy models as tools to analyse energy systems and pathways. Section 1 outlines various challenges for decision making that models may help address. It highlights that models rely on numerous assumptions and require transparency to avoid misinterpretation or miscommunication. Section 2 defines the term 'integration' as it is applied in this thesis, and interprets it in the context of energy system modelling. Section 3 explains the level of integration addressed within the three main parts of this thesis. Section 4 presents a categorisation of energy modelling approaches. Section 5 provides background information on modelling tools frequently referred to in this thesis before Section 6 concludes this introduction. Further detail regarding some of the modelling categories is provided in Annex A.

1 The Need for Energy Systems Analysis

Energy is deeply integrated into the fabric of our economies and everyday lives. We rely on energy to power our industries, meet our transportation needs, regulate the temperature of our buildings, and ensure the operation of our appliances. Still, close to 1.3 billion people lack access to electricity, and 2.6 billion people do not have clean cooking facilities at their disposal [1]. Without affordable access to modern forms of energy, their development will continue to be significantly hampered. Further, poverty, which is often associated with a lack of access to energy services, generally increases a population's vulnerability to the adverse effects of climate change [2]. These adverse effects are likely to increase, since global average temperatures are expected to rise by 2.8 °C to 4.5 °C if no countermeasures are taken [3]. The energy system contributes with over two thirds of the total global greenhouse gas (GHG) emissions. Accelerating access to energy while securing the current and future supply of climate-friendly energy are therefore key policy goals to ensure development and mitigate climate change.

1.1 Selected Complexities

The means to achieve these goals in a balanced manner are not trivial. According to the Global Energy Assessment [2], the world's future energy use over the next decades to 2050 will exceed all recorded consumption in history if current trends prevail. A major transformation of our energy systems is required to ensure a sustainable supply of energy. Many complex and diverse issues need to be addressed when trying to assess the extent of this transformation, *inter alia*[2]:

- **Economy:** Economic development and population growth rates are key drivers for energy system advances. Estimating how our economies evolve is central to assessing future energy demand [1]. Economic considerations are also closely related to decisions on how to meet demand. For example, capital-intensive investments in technologies with long payback periods are more likely to occur in economies with access to an adequate choice of financial instruments [4]. Further, interrelations between various sectors of an economy may require consideration. The scale and types of investments in the energy system will for example affect the employment situation across the economy [5], and job creation may be an important argument when designing policies to steer such investments [6].
- **Resources:** Once the demand for energy is estimated, the analysis of its supply should be matched with the available resources. This requires assessments of locally and internationally available reserves and resource potentials, including cost estimates for their exploitation. The final choice of the resources used further depends on environmental, social and economic considerations. The market price of resources has a significant influence on related technology investments and vice versa. For example, the U.S. shale gas revolution led to lower gas prices and replacements of

[2] In this thesis, political, market and environmental issues were considered by aligning some of the case studies closely with available energy strategies and country development plans. Similarly, economic development and associated energy demand growth were either aligned with government projections or compared with previous modelling efforts. Resource availabilities, technological developments and related costs were taken from the literature, coordinated with national research institutes and derived from own modelling approaches. Assumptions regarding the consumer acceptance of demand-side integration are mentioned in Section 2.4 of Part A. Further assumptions are discussed in detail when presenting the model applications in Part A, B and C of this thesis.

coal-fired with gas-fired power plants [3]. Apart from energy resources, links to other resource systems such as land-use and water require consideration to ensure an overall efficient resource management.

- **Technology:** A range of alternative technologies exist to exploit these resources and meet demand for energy services. Technological developments may significantly influence the economic viability of resource extractions. For example, improvements in hydraulic fracturing were one of the triggers for the U.S. shale gas boom [7]. End-use technologies may further strongly influence the shape of daily demand profiles. For example, shifting from compression to adsorption cooling fuelled by a district heating and cooling system may reduce daily variations in electricity demand [8]. Advancements in so-called 'Smart Grids' may further enable a better integration of end-use technologies. They might allow utilities to deliver energy services such as heating or cooling rather than merely electricity. Utilities may therefore profit from the increased flexibility in when to meet these service demands [9]. Further, many future technologies like algae biofuels or carbon capture and storage are on the horizon, sometimes with limited information about their future performance characteristics and potential cost implications.
- **Environment:** The main driver for investments in clean energy technologies may be climate policies. While many uncertainties are involved, it is estimated that additional investments of 16 trillion USD are required to meet the global climate change target of 2.0 °C [1][3]. Further, adaptation measures like desalination and increased pumping for agricultural irrigation may affect energy demand, and increased water diversions from reservoirs may decrease the hydropower storage potential. In addition to climate change related impacts, ambitions to curb negative local environmental implications from energy systems may also strongly affect future technology choices.

[3] Climate change mitigation may trigger considerable co-benefits with regard to energy sustainability, e.g., by increasing energy security and environmental impact [10]. A prioritisation of climate change as the sole objective of energy planning should however be avoided, as it may lead to deficiencies in achieving other socio-political and economic targets [11].

- **Public Acceptance & Consumer Choices:** Economic, technical and environmental attributes are not the only criteria for technology investments. For example, consumers may not choose to invest in economically profitable energy efficiency measures due to various barriers, such as high upfront costs combined with lack of access to finance. Further examples of barriers include lack of information and an unbalanced distribution of costs and benefits between stakeholders [12]. Public acceptance is also a key factor to consider. For example, limited experience exists regarding consumer acceptance of the closer demand-side integration that Smart Grids are expected to provide. What is acceptable may further differ significantly from one country to another. For example, Sweden had two municipalities competing for a final repository for spent nuclear fuel [13]. Such a situation is unthinkable in Germany, which is known for its strong anti-nuclear movement that ultimately facilitated a nuclear phase out until 2022 [14,15].
- **Geopolitics, Policies & Markets:** Foreign relations and associated energy security considerations may strongly affect a country's or region's acceptable level of energy dependence. For example, pipeline projects to connect the European Union (EU) to gas reserves in Azerbaijan gained in attractiveness in response to the conflict over gas exports from Russia to Europe via the Ukraine in 2009 [16,17]. Politics may further strongly influence the design of energy markets and could cause significant distortions. For example, to ensure affordable and secure supplies, global fossil fuel subsidies are currently roughly six times higher than those for renewable energy [1]. Through shaping the design of emission markets such as the EU Emissions Trading System (ETS), policies influence the emission price and thus the associated investments in clean energy technologies. The parallel implementation of national renewable energy policies may however confine the effectiveness of such trading schemes. For example, the German Renewable Energy Sources Act (EEG) and its feed-in tariffs have been criticised for their overlap with the EU ETS [18]. Further, energy policies may accelerate access to clean and affordable energy, for example, through clear targets and dedicated funds and finance mechanisms which help consumers afford the high upfront costs when switching to cleaner fuels [2].

Many hypothetical future energy system designs might form a functional basis of our future economies. However, identifying the most effective design becomes a challenge as the complexities involved are also afflicted with uncertainties. Yet, they require consideration to ensure that the information that underpins future energy investment strategies and policies paves the way towards economically efficient, environmentally friendly and socially acceptable energy systems.

1.2 Models as Tools to Inform Energy Strategies

Computer aided energy modelling as further described in Section 4 of this introduction has been used since the mid-1970s to assess future energy system designs and pathways [19–22]. Models commonly serve as test-beds to investigate system configurations and developments which would be impractical, too expensive or impossible to test in 'real-world' conditions [23]. Modelling may be described as an art rather than a science and results of long-term energy models are not predictive. Yet, if designed correctly and applied with due diligence, they may represent economically, thermodynamically and environmentally consistent energy system scenarios.

Scenarios may however be functionally predictive in the short-term, e.g., when a utility applies a model to optimise its day-ahead dispatch. Scenarios applied for long-term energy system analysis are more likely to be exploratory. For example, they may be set up to test out hypotheses regarding technological development or operational strategies (refer to Section 4.2.4 of Part B), to test the impact of various policy instruments like a transport fuel tax [24], or to investigate the energy system's resilience to certain shocks, like interruptions of the gas supply [25]. In addition to such exploratory elements, long-term models are often set up to assess how best to achieve certain strategic design criteria and targets. Such criteria and targets may include maintaining the availability of adequate supply infrastructure while fulfilling greenhouse gas emission reduction targets [26].

As we are attempting to represent an unknown future, models are characterised by a suite of simplifications and assumptions. It is good practice to reveal at least those which may significantly influence results. This is required to promote adequate result interpretation, especially by those not involved in the modelling process.

For example, assumptions about the diffusion of energy efficient technologies will strongly influence energy demand. This, in turn, has implications on investments in energy conversion technologies, resource use and associated emissions. Further, the model's boundaries, i.e., which aspects are included or excluded, may significantly influence results. For example, a regional model may calculate greenhouse gas emission reductions in response to the introduction of a carbon tax. Yet, if the model boundaries are not adequately chosen, it may not be possible to assess the risk of 'carbon leakage', i.e., the compensation of some of the reductions by increases in another region. This may for example be due to the resulting increases of fossil fuel costs, which may cause polluting industries to shift some of their production to other regions with less stringent regulatory frameworks.

Given their different simplifications and assumptions, variations in the results of long-term models may be significant. This is demonstrated by comparative studies by Hake et al. [27] for Germany and by Krey and Clarke [28] for global energy-economic and integrated assessment models. Scenario comparisons, sensitivity analyses and probabilistic assessments allow taking the uncertainties associated with some of the assumptions into account. This might help to highlight those strategies which perform well under a wide range of potential future developments. For example, this may serve to assess the flexibility and robustness of energy systems, i.e., the extent to which they facilitate future adaptations and perform well under various potential developments [29].

Due to the numerous abstractions required, communicating modelling results is challenging, but a key requirement to ensure their usefulness for policy making [30]. Communication needs to vary depending on the audience. While policy makers might be satisfied with a concise summary, a third party wanting to challenge the modelling results requires much more detail. Transparency is key in helping ensure the credibility of modelling processes. If not accounted for, there may well be no way for an external audience to reliably identify the main drivers of the results [31]. To avoid potential misinterpretations, all modelling assumptions and code applied in this thesis were made public and are presented as part of this thesis.

2 Integration

Integration may be defined as "the act of combining or adding parts to make a unified whole" [32]. This implies that considering integration is increasingly important the more holistic an assessment should be. The nature of the parts which need to be combined or added to make a unified whole depends largely on the context. Jakeman and Letcher [33] and Kelly (Letcher) et al. [34] provide a categorisation in the context of integrated assessments. According to them, integration can be considered between:

- Social, economic and environmental issues,
- Stakeholders and knowledge,
- Disciplines of natural and human science,
- Processes or models, and
- Temporal and spatial scales of consideration.

None of these categories is necessarily mutually exclusive. Considering integration within one category might in fact not be possible without considering integration within another.

Models are applied to gain insights into parts of such 'a unified whole'. Ultimately, this unified whole may include our economies and their interrelations with the wider environment. Assessed parts thereof may be our power systems, our energy systems, or our resource systems in general. The appropriate level of integration within and between these aspects varies with the investigation at hand.

Based on the case studies presented in Section 5 of Part B and in Part C of this thesis, it seems evident that too weak integration may result in incomplete analysis and potentially misleading insights. Derived conclusions may therefore be misleading and might not allow reaching a desired future state most effectively – or at all. Yet increased integration may not be a panacea. Too much integration might give a false sense of accuracy. Further it will result in increasingly complex models. Such models are likely to be significantly more time-consuming to develop, might challenge the available computational power, may be inflexible to adjust to changing assumptions, and might be more difficult to interpret.

Deciding on the appropriate level of integration requires striking a balance between simple and flexible versus more accurate and holistic approaches.

3 Objectives, Structure and Contribution of this Thesis

3.1 Objective

In their current state, long-term energy models are broadly applied from sub-national to global planning. The model applications may consider various aspects of integration as defined in Section 2 of this introduction. For example, they may consider the implications of policies, may account for emissions, and calculate the economic performance of technologies. Refer to Sections 4 and 5 of this introduction for a discussion of different model families and tools.

Building on publically available models, the overall objective of this thesis is to enhance the level of integration considered in long-term bottom-up energy system models beyond what is typically considered within a single off-the-shelf tool. Levels of integration were added in a quasi step-wise approach as outlined in Fig. 1. This thesis further aims to demonstrate the implications of the increases in integration on modelling results and conclusions.

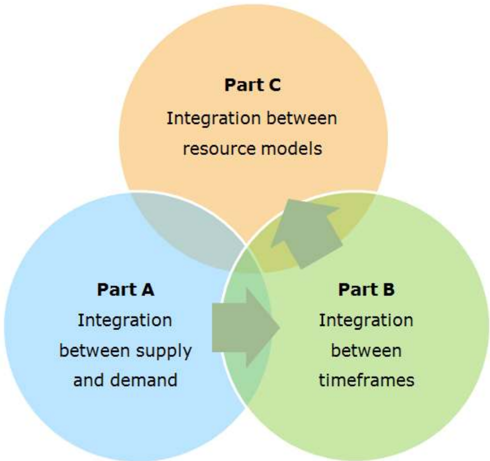

Fig. 1: Elements of integration as considered in this thesis

3.2 Academic Contributions

Part A of this thesis focuses on the increased integration between electricity supply and demand that might be facilitated by Smart Grids. Various attributes related to Smart Grids have been modelled in depth [35–38]. Yet, a comprehensive and openly available modelling framework to assess Smart Grid solutions at an energy system level is neither easily found [39], nor typically applied to assess electrification options in developing regions. Lean[4], transparent and open tools like OSeMOSYS may be easily accessible to test out and communicate new hypotheses and modelling approaches related to Smart Grids.

Accordingly, OSeMOSYS was extended in Part A to be able to assess the potential energy system implications of selected elements which may form part of Smart Grids. More specifically, these elements include variable electricity generation, a prioritisation of demand types, flexible demands, and storage devices. The model extensions are explained comprehensively at various levels of detail, from a conceptual overview to the code implementation. Smart Grids may offer opportunities for developing countries to accelerate access to electricity services [40]. This might include elements which are at the focus of attention in developed countries as well as options which specifically address the needs of developing countries. A selection of such elements and a qualitative preliminary assessment of their potential are further presented in Part A.

Part B discusses the need for increased integration between temporal scales. Due to their long-term outlook and coarse temporal resolution, high-level long-term energy system planning tools usually do not focus on the time scales associated with short-term variability of supply and demand [41]. They may therefore misrepresent the investments required to balance this variability [42]. A separate suite of electricity market simulation models and operational power system tools is specifically designed and has successfully been applied to investigate short-term variability [36,43–45]. However, these tools commonly exclude non-electricity sectors like heat or transport, or may focus on operational aspects of power systems rather than capacity investments. To address this gap, long-term energy system are sometimes interlinked with power system tools [29,45–50].

Part B demonstrates an approach to capture the key implications of short-term operating requirements within a single long-term energy system model. This enables insights regarding optimised future capacity investments while ensuring the system's flexibility to balance variability. Specifically, an approach to consider the contribution of wind power installations to the system adequacy is implemented in OSeMOSYS [51]. Further, this tool was extended to ensure the

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4 With a concise code adjusted to the investigation at hand. While such a 'lean' tool may have less functionality compared to traditional long-term models, it comes without any organically grown code legacy.

power system's capability to balance short-term upward and downward power variations across two timeframes. This capability is modelled based on user-defined demands for so-called operating reserve services, and technology specific minimum stable operation levels, operating reserve contributions and cycling characteristics. The model enhancements were then tested in an application and benchmarked against a more detailed short-term electricity system model of Ireland.

Part C focuses on integration between energy and other resource systems. Climate, energy, land-use and water systems are highly linked. Efficient management of these resources requires a consideration of such links to avoid an uncoordinated resource use and potentially conflicting resource policies [52]. Government structures and the associated division of responsibilities are not often established with the ability to capture these linkages [53]. Historically, related decision-making is often based on fragmented assessments of resource systems and their interdependencies are rarely taken into account. Yet, models would offer useful tools to assess integration between resource systems, as demonstrated extensively in the literature [54–64].

Part C demonstrates the importance of considering resource linkages by assessing the added value of this form of increased integration. This was achieved by comparing results from an energy model considering climate change assumptions with those of an interlinked land-use, energy and water model. Mauritius served as a case study for the application of this modelling approach. The broad co-authorship of the underlying papers helped integrate a relatively wide set of perspectives. The author of this thesis contributed to this effort with the configuration of the energy model and the interpretation of its results. In response to this broader effort, the Government of Mauritius has announced the appointment of a so-called 'high-level CLEWS panel'. This was set up to ensure coherent policies between Climate, Land-use, Energy and Water strategies (CLEWS) [65].

The term integration is extensive and may be interpreted differently depending on the context. This is reflected in the various existing tools and approaches applied to consider integrated planning [54,66,67]. Only a subset of the issues related to integration could be taken into account in this work. Refer to Section 2 of the concluding chapter of this thesis for selected examples of how this work could be extended.

4 Modelling Families

Numerous specialised models have been developed to inform the design of energy strategies, focusing on issues such as policies, investments and operational aspects. This section presents some families of such modelling tools as background information to the analysis that follows. The methodology for considering aspects of integration with these tools is described in detail in Section 2.2 of Part A, Section 2 of Part B and Section 2 of Part C of this thesis.

Note that the presented modelling families are exemplary and by no means definitive or exhaustive. Various potential categorisations exist, each of which may be interpreted differently depending on the context and the author's perspective (refer to Section 4.1 of this introduction).

One way to categorise energy models is by their scope. Some focus on the entire energy system, others single out the power system. Some are specifically applied to focus on short-term dispatch and operational issues, other to assess long-term investment decisions. Some models cover only supply or demand, others both.

Energy models can also be grouped in aggregated top-down economic or disaggregated bottom-up engineering models [68]. Top-down models draw on macroeconomic relationships to derive and inform insights. They can be especially useful to assess the effects of cross-sectoral policies like carbon taxes or fuel subsidies [69]. A typical characterisation of top-down models includes [70]:

- Econometric models
- Input-output models
- Computational general equilibrium models

Econometric models draw on statistical analysis of historical time-series as a basis for future projections [68]. This type of models may base their projections on variables such as gross domestic product (GDP), population, or energy prices [71]. Input-output models consider the interrelations within an economy by capturing the monetary or commodity flows between various sectors. They usually provide a static snapshot of an economy. Computational general equilibrium (CGE) tools are dynamic models which ensure that an economy wide general equilibrium between sectoral demands and supplies occurs. Top-down models were not applied or drawn on in this thesis due to their lack of technological detail. Further explanations on input-output and CGE models are provided in Annex A.

The main focus of this thesis is on bottom-up models, as they enable a more detailed representation of technologies within the energy system. They are therefore particularly valuable for investigating issues such as the role of individual technologies or energy sector specific policies such as technology or emission targets. Bottom-up models are characterised by their reliance on thermodynamic relations between the production, conversion and use of energy carriers. In general, they do not take cross-sectoral interdependencies into account. A typical characterisation of bottom-up models applied and extended in this thesis includes [72]:

- Accounting frameworks
- Simulation models
- Optimisation models

Accounting frameworks calculate physical flows of energy carriers within the entire energy system. They are entirely driven by exogenous assumptions about the interrelations within the energy system. Simulation models simulate the energy system based on specified rules for behaviour, operation and investment. Optimisation models calculate system investments and operations by maximising or minimising an objective function subject to a set of constraints. They may calculate a partial economic equilibrium if they include sufficient detail to derive dynamic balances between the supply and demand of commodities [70,73]. The overall optimisation across all technologies of the energy system differentiates them from simulation models. Further differences between these bottom-up models are delineated further in the chapters 4.2 – 4.4 of this introduction.

Bottom up and top down models have different strengths and weaknesses [70], due to which they may be strongly complementary. The consideration of economic feedback loops in top-down models may enable an understanding of the impacts of energy policies on the broader economies of a nation, a region or the world. This enables insights regarding macroeconomic effects such as structural changes, overall economic activity or employment. The rather generalised information derived from top-down models may be complemented by details derived from bottom-up models. These models are highly data dependent and rely on many assumptions. Yet, the aggregated information from such models may help inform top-down analysis with respect to capital flows, non-monetary barriers and intra-sectoral structural change.

Even within bottom-up modelling tools such complementarity is strong, for example between energy and power system models. A simplified illustration of this complementarity is suggested in Fig. 2. The investment decisions and policy recommendations derived from a long-term bottom-up model may serve as input for a market simulation model. The market model may assess a shorter time period with a much higher temporal resolution to calculate electricity prices and reliability indicators. Derived extreme load and demand combinations may serve as input for so-called 'electric power system models' with a strong electrical engineering focus.

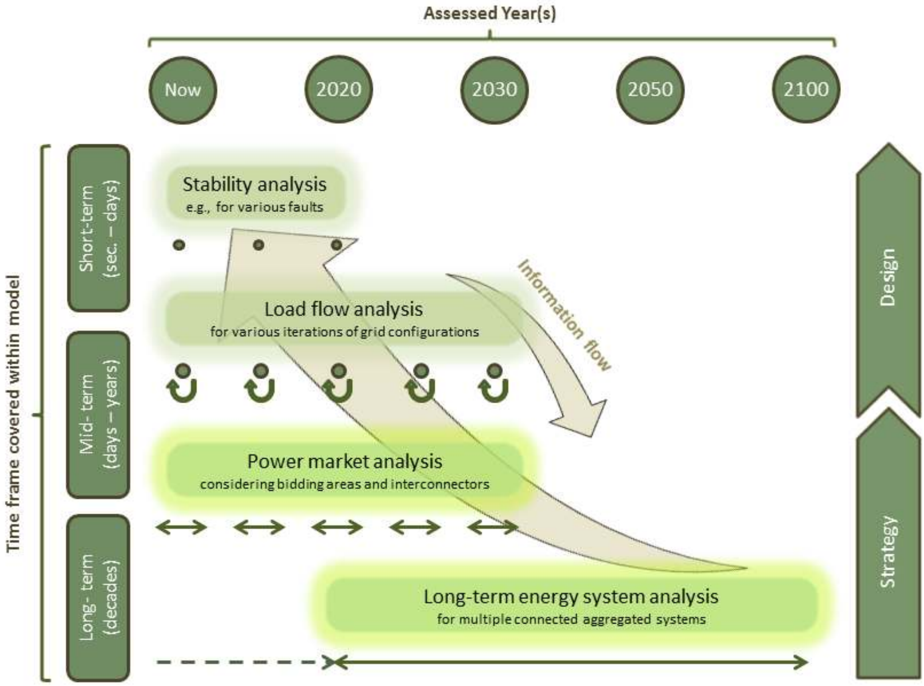

Fig. 2: How energy system models may inform power systems analysis

The focus of this thesis is on long-term bottom-up energy system analysis and to a limited extent power market analysis. The figure is based on discussions with Jørgensen P. from the Danish Transmission System Operator (TSO) (personal communication, 10 October 2013) and represents a general tendency, rather than a strict categorisation.

Models focusing on AC or DC load flow analysis may serve to investigate various grid configurations. Such models may cover timeframes of hours or years. Based on the derived transmission capacities, steady-state, transient or dynamic stability analyses may serve to assess disturbances in power systems. Stability analyses usually cover timeframes of up to several minutes. They may provide important insights on the design of the components of the transmission and distribution system. Andersson [74] provides some examples of approaches to model electric power systems.

While energy system models may implicitly inform stability analyses, in general the opposite is not necessarily true, i.e., the overall future mix of generation and demand-side technologies as calculated by energy system models might not be affected by the results of stability analyses. As the focus of this thesis is on analysing the composition of future energy systems, electric power system models are not directly considered as an integral part. However, in some cases they may suggest limits to the future penetration of individual technologies within power systems. Such models may therefore inform the set-up of long-term energy system models. For example, results from such tools were used to limit the maximum instantaneous penetration of wind power in a case study on Ireland (refer to Section 5.6.1 of Part B).

4.1 The Value of Such a Categorisation

Allocating energy modelling tools to one of these families is particularly difficult as many flexible hybrid tools evolved which combine several elements of different modelling families. For example, the model LEAP can combine elements of an accounting framework with those of an optimisation or simulation model based on macroeconomic assumptions [75]. Refer to Section 5.4 of this introduction for further details on LEAP.

Further, while a production simulation model does not need to be an optimisation model, all optimisation models rely in one way or another on an underlying production simulation model. Optimisation models may as well be combined with a simulation approach, for example, by modelling different technology pathways in different model runs [76]. This approach may be applied to investigate the value of certain technology mixes which the model initially did not consider as cost-optimal. As another example for hybrid approaches, the results of econometric analyses may serve as inputs to other top-down as well as bottom-up models [77].

Also the terms bottom-up and top-down models may be used differently depending on the context. For example, from an engineering perspective, even models considering individual power plants may be categorised as top-down if plants are treated as black-boxes [28]. Further, while simulation models are grouped as bottom-up models in this thesis, the term may as well be used to refer to top-down macroeconomic models based on input-output tables [78].

A categorisation of modelling tools is further complicated by the various names which are often used to describe one and the same model. For example, when focussing on the entire energy or power system, certain linear optimisation models may be referred to as capacity expansion or partial-equilibrium models. While not necessarily interchangeable, these terms are not mutually exclusive. Yet, only one out of several possible terms may be presented when describing a model.

As many modelling tools exist, the categorisations of bottom-up models detailed in the following chapters are useful for communicating the main underlying principles between analysts. It should be noted that the tools within any one of these categories can be highly divergent. For example, a report by the Intergovernmental Panel on Climate Change (IPCC) notes that differences in the input assumptions applied in models within one modelling family may be more significant than the structural differences between the modelling families [79].

4.2 Accounting Frameworks

Accounting frameworks capture the physical flows of various energy carriers and ensure that energy and thermodynamic balances are obeyed. They may take the form of spreadsheet based tools and often serve as a depository for large databases and for results processing [38]. Models which are generally referred to as accounting frameworks include MAED [80] or elements of LEAP (refer to Section 5.4 of this introduction).

Accounting frameworks are based on verifiable, exogenously defined interrelations between components of the energy system. They are frequently applied to assess the differences between various scenarios. All elements and interrelations considered within an accounting framework are defined by the analyst. The resulting simplicity of the accounting frameworks is a main advantage and enables transparency regarding the applied assumptions [77]. Yet, ensuring the consistency of the corresponding input data and assumptions with the applied scenarios requires a thorough understanding of the energy system. All other bottom-up energy system models build on elements of accounting frameworks as a basis for their analysis.

4.3 Simulation Models

4.3.1 Energy System Simulation Models

A simulation model simulates the energy system and its operation [81]. For example, simple rules for the dispatch of technologies or future investments may be considered. However, simulation models combine a variety of different modelling approaches [72]. They may consider decentralised, microeconomic decision-making of the individual players in energy markets [38], drawing on game theory and agent-based modelling to simulate adaptive systems [82,83]. They may simulate consumer and producer behaviour in response to drivers such as income, energy security, public policies and endogenous energy prices. All players may pursue and optimise their own goals individually. The overall outcome at system level may therefore diverge from an overall energy or electricity sector-wide optimum.

EnergyPLAN constitutes one example of a simulation model [84]. It enables an exogenous specification of electricity market prices [84]. Another well-known example is the World Energy Model (WEM), which informs the International Energy Agency's (IEA) World Energy Outlook [85]. It is driven by econometrically derived assumptions regarding sectoral energy demands. These are based on macroeconomic estimations regarding economic growth, demographics, fossil fuel prices and technological developments. Due to its combination of macroeconomic approaches with the simulation of explicit technology choices, the WEM might be classified as a hybrid model [70].

4.3.2 Production Simulation Models

Production simulation models may be interpreted as a subset of simulation models. They are specifically designed to calculate the power systems' dispatch and costs of generating electricity [86]. They are also frequently applied to assess related power system characteristics such as its reliability and emissions. Depending on the focus of their application, production simulation models may be referred to as dispatch models, unit-commitment models, short-term planning models, or operational power system models. Solving methods range from sorting units based on a predefined merit order to advanced approaches like genetic algorithms, dynamic programming and linear and mixed-integer programming [87].

Production simulation models may be based on time slices, load distribution or load duration curves. Time slices combine representative times within a year (refer to Section 2.2 in Part A for further explanations). A load-duration curve specifies the number of hours a certain load is exceeded [88].

Commonly, production simulation models analyse a predefined power system configuration, as opposed to the expansion of capacities. Naturally, production simulation models will therefore focus on shorter timeframes and model the dispatch in more detail than capacity expansion models. Due to these characteristics they might also be applied to check the accuracy of results of capacity expansion models, as explained in Section 1.4.3 of Part B of this thesis and further demonstrated in Section 5.2 of Part B.

One way to classify production simulation models is by the way they consider power plant availabilities.

4.3.2.1 Derating Method

This method is the simplest approach to consider power plant availabilities. Forced outages are implicitly taken into account by defining average available power plant capacities. These derated capacities are applied throughout the dispatch period to deterministically[5] calculate the generation mix. Due to its simplicity and fast calculation times, the derating method is commonly integrated into long-term energy system simulation and optimisation models (refer to Sections 4.3.1 and 4.4 of this introduction).

The disadvantage of the derating method is that the importance of fast ramping power plants for compensating generation outages may be significantly underestimated [86]. Further, system indices such as the Loss of Load Probability (LOLP) may not be assessed. The LOLP is defined as "the probability that at least one consumer is involuntarily disconnected due to capacity limitations in the system" [89]. These short-comings are addressed by the more comprehensive probabilistic production cost and Monte Carlo simulations.

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5 I.e., no randomness occurs in the sense that the same set of input parameters will always calculate the same output values.

4.3.2.2 Probabilistic Production Cost Simulation

Probabilistic production cost simulations draw on probability distributions of, for example, forced power plant outages, demand and wind power availabilities. They are frequently applied to deterministically derive the expected operating costs and system reliability indices. Probabilistic production cost simulations usually do not require significant computational power and solve rather fast and accurately [90]. However, load and outages are assumed to be statistically independent, which may not be the case in reality. For example, some correlation between wind availabilities and load may occur [91]. Further, only a single region may be modelled as the transmission grid is basically not considered [89].

4.3.2.3 Monte Carlo Simulation

Monte Carlo simulations use random samples to analyse a mathematical problem [92]. Applied to production simulation models, these samples may constitute the outages of power plants or transmission lines throughout a year. Due to the randomness introduced, different model runs will results in different solutions. However, programs may enable the user to define a 'random number seed' to reproduce the exact same sequence of random numbers [93]. While a single solution may often be preferable, the results of Monte Carlo simulations may in many cases be closer to real-world situations. Commonly, multiple runs with different sequences of random numbers are performed to assess the properties of a system. Variance reduction techniques may be applied to decrease the number of iterations required for achieving a certain precision [89].

4.4 Optimisation Models

Optimisation models endogenously calculate energy system attributes such as, amongst others, the required technology investments and dispatch. They are driven by an objective function subject to various physical, technical, environmental, economic and policy constraints. Frequently, they may be applied to minimise costs or to maximise total welfare, i.e., the sum of consumer and producer surplus. If demand for electricity is inelastic, i.e., price independent, these two formulations will derive the same results [94]. The sector-wide optimisation constitutes the main difference to simulation models. The objective function is commonly optimised using linear or mixed integer programming approaches. Optimisation models may however include aspects of other bottom-up modelling tools. For example, they may use some of the techniques described in Section 4.3.2 of this introduction to simulate the power sector.

Apart from minimising costs, a model might also optimise other objective functions, for example, to minimise environmental impact or to maximise access to electricity at a given cost. Multiple objectives may be considered. This might be achieved with an explicit multi-attribute objective function, where any form of weighting is assigned to each attribute [29]. Alternatively, this may be implicitly considered by associating costs to system attributes. For example, environmental objectives may be considered through emission taxes. Non-cost objectives may be implemented as a constraint, e.g., as a cap on emissions.

If applied to the whole energy or power sector and when considering demand levels which vary as a function of cost, optimisation models may be categorised as partial-equilibrium models. The term 'partial-equilibrium' refers to the calculation of an economic equilibrium of supply and demand within these sectors, but without considering any interactions with the broader economy. In general, applying an optimisation model implicitly represents a market structure with the following characteristics [89]:

- **Perfect competition:** All players in a market compete against each other and supply their electricity at their marginal production cost, i.e., they are assumed to be price takers.
- **Perfect information:** All decisions by the market players are based on perfect information about parameters influencing their decisions. This includes perfect foresight into the future.
- **Economically rational consumer behaviour:** Technologies with the cheapest life-cycle costs are invested in [38]. In reality, the lack of investments in energy efficient technologies demonstrates that consumer choices are not merely based on economic decision criteria.

These characteristics results in an energy market representation where no distorting effects like misuse of market power occur. Optimisation models describe an ideal state which may guide the development of policies and regulations aiming to bring real-world energy systems closer to such an ideal state. While ideal, an array of constraints may be applied to help derive insights which better reflect real-world conditions. One of many such conditions is the market actors' lack of perfect foresight. In reality, certainty of investment does not exist and risk needs to be priced in. A private investor may therefore prefer less profitable technologies with a shorter pay-back period over more profitable long-term investments which are afflicted with a higher risk. A simple way to model this behaviour is by defining technology specific discount rates to be higher than the expected cost of capital. Aspects of limited foresight may as well be considered in optimisation models by setting the decision horizon to be shorter than the full modelling timeframe [95]. Sequential decision making may then be implemented by splitting a single optimisation model into sub-problems for each decision horizon.

For each set of assumptions, optimisation models typically calculate one single solution with regard to future investments in energy system technologies and their operation. Sometimes it may therefore be useful to investigate the near-optimal solution space to identify maximally different system configurations which still perform well with regard to the modelling objectives. This approach is further explained by DeCarolis and by Trutnevyte [96,97].

Further, uncertainty may be addressed by probabilistic analysis drawing on stochastic programming techniques [29]. For example, Monte Carlo simulations (refer to Section 4.3.2.3 of this introduction) may be applied to assess forced outages of power plants. Further, probabilities may be assigned to different future states of the world. For example, such states could represent the uncertainties regarding the scale of future emission reduction targets. An optimisation taking these probabilities into account may then derive a flexible energy system configuration which performs best considering this various potential future states [98]. As in all other modelling families, uncertainties can as well be addressed through scenario and sensitivity analysis.

Examples of optimisation models include OSeMOSYS, MARKAL, TIMES and MESSAGE. Further, while not typically listed in this category, LEAP enables an optimisation which is limited to the electricity system. All of these tools are introduced in more detail in the following section.

5 Modelling Tools Used or Extensively Drawn from in this Work

This thesis mainly draws on bottom-up models, as they enable detailed assessments of the future role of individual technologies. Numerous tools exist, from specialised proprietary models developed by institutes for their own use to wide-spread tools with a vast field of applications. Depending on the institutions developing the models, they may be open source, commercially available, proprietary, or not shared at all. In this section, selected tools which are frequently referred to in this thesis are described in more detail. The reader is referred to the literature for comparisons of numerous additional tools [22,36,38,81,99,100].

5.1 OSeMOSYS

OSeMOSYS is an open source energy system optimisation model with a medium- to long-term time horizon. It is repeatedly enhanced in this thesis to test out new modelling approaches, as demonstrated in Section 2 of Part A and in Part B. As indicated in these sections, various 'core versions' of OSeMOSYS were used as starting points for these modifications. The applied core versions always constituted the latest publicly available versions at that time. Elements of the enhancements presented in this thesis were integrated into later core versions of OSeMOSYS, which then served as new starting points for succeeding modifications. As such, this thesis also documents important elements of the progress of OSeMOSYS over the period 2011 – 2013.

OSeMOSYS was used for these enhancements as it conveniently enables modifications due to its rather short, well documented and clearly structured code. Functional 'blocks' as illustrated in Fig. 3 combine sets of equations, for example, to model storage. Multiple levels of abstraction are used to describe these blocks, ranging from a (1) conceptual description to the (2) mathematical, algebraic formulations, the (3) actual code implementation and its (4) application [101].

OSeMOSYS is designed as a tool to inform the development of local, national and multi-regional energy strategies. It covers all or individual energy sectors, including heat, electricity and transport. It is a deterministic linear optimisation model and minimises the total discounted costs. Mixed integer programming may be applied for certain functions, like the optimisation of discrete power plant capacity expansions.

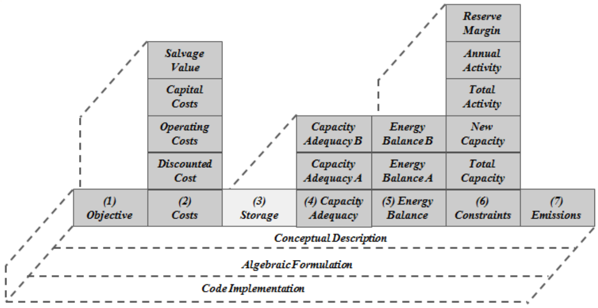

Fig. 3: OSeMOSYS 'blocks' and levels of abstraction; Adapted from Howells et al. [101]

The model is driven by exogenously defined demands for energy services. These can be met through a range of technologies which draw on a set of resources, defined by their potentials and costs. On top of this, policy scenarios may impose certain technical constraints, economic realities or environmental targets. As in most long-term optimisation models, OSeMOSYS in its standard configuration assumes perfect foresight and perfect competition on energy markets.

The model is characterised by a wide and flexible technology definition. A technology comprises any fuel use and conversion, from resource extraction and processing to generation, transmission and distribution, and appliances. It could therefore refer to, for example, an oil refinery, a hydropower plant or a heating system. A technology can be defined to consume and produce any combination of fuels. Each technology is characterised by numerous economic, technical and environmental parameters, for example, investment and operating costs, efficiencies, availabilities, and emission profiles. Outages are usually considered by derating capacities as described in Section 4.3.2.1 of this introduction.

The OSeMOSYS model code is written in GNU MathProg, a high level mathematical programming language [102]. The open source solver GLPK may be used for the mathematical optimisation of the model [103,104]. Both the OSeMOSYS model and the GLPK solver do not require any upfront financial expenditure. GLPK can as well produce an MPS file for use with a more powerful solver[6]. Diverging from commonly applied programming conventions, rather long parameter and variable names are used in OSeMOSYS. This ensures that formulas can be read in a rather self-explanatory manner and simplifies the familiarisation with the OSeMOSYS code for those new to this modelling tool. For consistency, all enhancements presented in this thesis comply with this naming convention.

In its extended version, OSeMOSYS comprises just above 400 lines code. In 2013, shortened versions of OSeMOSYS have been released. The merging of equations significantly improved the performance without affecting the model's data requirements or results. However, it reduced the readability of the code. Therefore, only the extended versions were applied in this thesis.

OSeMOSYS is developed in collaboration with a range of institutions, including the International Atomic Energy Agency (IAEA), the United Nations Industrial Development Organisation (UNIDO), KTH Royal Institute of Technology, Stanford University, University College London (UCL), University of Cape Town (UCT), Paul Scherrer Institute (PSI), Stockholm Environment Institute (SEI), and North Carolina State University.

Several user interfaces are currently available or under development. For example, OSeMOSYS is well integrated into LEAP (refer to Section 5.4 of this introduction), which applies a limited set of OSeMOSYS' optimisation features for power plant capacity expansion planning [105]. An alternative interface is currently being developed by Noble-Soft Systems. This ANSWER interface is similar to the one used for the frequently applied long-term models TIMES or MARKAL (refer to Section 5.2 of this introduction) [106]. As opposed to LEAP, ANSWER supports most of the functionality provided by OSeMOSYS and thus enables an optimisation across the entire energy system. If the full scope of OSeMOSYS is required, or if adjustments are necessary, OSeMOSYS can as well be set up as text files.

While the development of OSeMOSYS initiated in 2008, its first detailed description was published by Howells et al. [101] in 2011. Some of the expansions presented in Section 2 of Part A of this thesis led to the current core version of the code as available at www.osemosys.org.

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6 For example, GUROBI offers free academic licenses.

5.2 MARKAL & TIMES

The Integrated MARKAL-EFOM System (TIMES) is an optimisation model similar to OSeMOSYS. It is driven by the same overall dynamics and minimises the total system costs, but builds on a longer history.

TIMES is developed by the Energy Technology Systems Analysis Program (ETSAP), which is an Implementing Agreement of the IEA [107]. Originally, TIMES evolved from the Market Allocation (MARKAL) model, which was initiated in the end of the '70ies. Both models are still used in parallel and frequently referred to as the MARKAL/TIMES family of models [106].

MARKAL and TIMES are frequently used in international research: according to Connolly et al. [81], they are applied in 70 countries by 250 institutions. Over 350 publications based on these two models are reported over the period 2008 – 2010 by ETSAP [108]. Several variants of both MARKAL and TIMES exist, for example MARKAL-MACRO, which couples MARKAL to a macroeconomic model [109]. Another prominent example includes the global TIMES Integrated Assessment Model for ETSAP contracting parties (ETSAP-TIAM), which covers 15 regions characterised by thousands of energy sector technologies.

The TIMES code is complex and comprises around 20,000 lines of code. A thorough overview of the TIMES model was prepared by Remme [110]. Loulou and Labriet [73] compiled a detailed description of TIMES and Loulou [111] further published its mathematical formulations. While its code is freely available, upfront expenditures are due for acquiring (1) the General Algebraic Modeling System (GAMS), (2) a GAMS compatible solver such as MINOS, CPLEX, XPRESS, GUROBI, CONOPT and (3) either the ANSWER or the VEDA interface. The reader is referred to Börjesson and Ahlgren [112] and Fakhri et al. [113] for exemplary applications of MARKAL for assessing policies and expansion strategies for biogas and district heating distribution systems.

5.3 MESSAGE

MESSAGE, the Model of Energy Supply Strategy Alternatives and their General Environmental Impacts, is a medium- to long-term modelling tool designed for energy system planning, policy analysis and scenario development [114]. It is an optimisation tool based on a mathematical paradigm comparable to the one of OSeMOSYS, MARKAL and TIMES. The model may optimise various objectives, including to minimise costs or environmental impact, or to maximise self-sufficiency [80]. Several standard solvers like CPLEX or GLPK may be chosen for this purpose [115]. Its time horizon is user-defined and results are calculated for each time slice and each year or group of years respectively.

While MESSAGE is in general driven by exogenously defined demands for energy services, it may be combined with a non-linear macroeconomic top-down module (MESSAGE-MACRO). This enables the endogenous calculation of price dependent energy demands based on the calculated total output of an economy. This output is calculated according to constant elasticity of substitution (CES) production functions with capital stock, growth rates of total labour and energy intensities as input values [116]. Refer to Annex A.2 for further information on production functions.

Several additional variants of MESSAGE exist. For example MESSAGE-Access is applied to assess scenarios focusing on accelerated access to electricity and clean cooking fuels. It focuses on poor and rural communities and considers consumer preferences for fuels and technologies.

The development of MESSAGE originally started at the International Institute for Applied Systems Analysis (IIASA) in 1976. The IAEA joint efforts with IIASA by developing a user-interface for MESSAGE and offering supportive capacity building for close to 3,000 people. The model is available for free for non-commercial use by IAEA Member States and 95 countries have signed a user agreement governing their use of MESSAGE [115]. MESSAGE and its variants have been used for various international assessments, including work for the IPCC, the World Energy Council (WEC) and the Global Energy Assessment (GEA) [114].

5.4 LEAP

LEAP, the Long-range Energy Alternatives Planning System, is a widely used medium- to long-term modelling tool for integrated resource planning [75]. It is applied to assess climate change mitigation strategies and analyse energy policies by investigating yearly capacity expansions. The underlying dispatch of technologies is calculated for each user-define time slice within a year.

LEAP is mostly used for comparing various future pathways to reference scenarios, from which other diverging scenarios inherit their main assumptions. Geographically, applications span across a wide range, from cities to national, regional and global models [117]. The model enables a consideration of various economic sectors, technologies, costs and emission profiles and comprises the entire energy supply chain, from resource extraction to processing, conversion, delivery and consumption. LEAP includes a Technology and Environmental Database (TED) which lists technology specific costs and performance data including emission factors [99]. As in the previously described models, technology outages are usually considered by derating capacities.

While LEAP may calculate energy demands based on top-down macroeconomic assumptions, it also facilitates technologically detailed representations of energy systems. It may therefore rather be categorised as bottom-up energy model [71]. Previously, it has been described as an accounting framework with elements of a simulation model [118]. While this is largely still true, since the LEAP 2011 version the user can choose to model the power sector drawing on the integrated optimisation features of OSeMOSYS. If this optimisation is not chosen, the order and scale of individual future capacity expansions has to be predefined by the analyst and LEAP will then decide in which year these expansions take place. In this case, all factors determining future development pathways are exogenously specified by the user.

LEAP dates back to 1980 and is currently developed by SEI [119]. It is applied by over 5,000 users in more than 190 countries [75,81]. LEAP licences for non-commercial use are freely available for modellers from developing countries. Over 200 publications are listed at its website which refer to LEAP or build on it for their analysis. The reader is referred to Rogan et al. [117] and Suganthi and Samuel [71] for exemplary applications of LEAP.

5.5 PLEXOS

PLEXOS is a commercial power system modelling tool used for electricity market simulations and was first released in the year 2000 [120]. It is a deterministic mixed integer linear programming model applying a quadratic optimisation [36]. PLEXOS minimises the expected costs of investments and the electricity dispatch considering: operational costs, consisting of fuel and carbon costs; start-up costs; and penalty costs for unserved energy and for not meeting reserve requirements.

The model is driven by a number of constraints, including energy balances, water balances for pumped storage hydropower, emissions constraints and constraints on unit operations. These include limits on the generation, reserve provision, up and down times and ramp rates. Several upward and downward reserve categories can be specified. Fuel consumption is calculated using piecewise linear functions as outlined in Drayton-Bright [121].

Forced outages and related security and contingency constraints are considered drawing on Monte Carlo simulation. The frequency and severity of forced outages are defined through forced outage rates and associated mean times to repair (MTTR) combined with Weibull distributions. Maintenance schedules may be optimised considering average maintenance rates and MTTR. Alternatively, power plant maintenance schedules can be specified exogenously.

The temporal resolution can be defined flexibly. It may range from interval lengths of one minute to multiple hours in hourly, daily or weekly steps over the full modelling horizon. Typical modelling periods may span over one year or more. To avoid issues with intertemporal constraints, e.g., related to the unit commitment of large units and storage end levels, a '*look-ahead*' period is used at the simulation step boundaries. The optimiser calculates the model variables for the simulation period and the look-ahead period, but only keeps results for the former.

The optimisation problem is created using AMMO, a mathematical language written for PLEXOS[7]. The problem is then optimised drawing on either of the CPLEX, Gurobi, MOSEK, or Xpress-MP solvers. PLEXOS is freely available to academic institutions for non-commercial research, apart from any additional costs for the required solvers.

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[7] AMMO's role is comparable to those of other mathematical languages such as AIMMS, AMPL, or GAMS.

Over 700 installations of PLEXOS are applied by 135 clients in 32 countries [122]. Apart from research institutions, its user base consists mainly of players in the power market such as utilities and system operators [44].

6 Concluding Remarks

It is noted that models are simply abstractions of reality that are useful to provide insights. They are subject to uncertainties, from the data that underpins them, to the appropriateness of the markets they represent, and the interpretation of drivers of energy system developments.

In addition to the various assumptions regarding input data, the models themselves are characterised by many simplifications. For example, multi-regional models with a long-term outlook often do not represent the dynamics of short-term national decision making processes in detail [28][8].

Another potential limitation of energy models is their scope. For example, the bottom-up models applied in this thesis do not consider the linkages between the energy system and the wider economy.

Energy system investments will lock us into a development pathway for many decades to come, given the long economic lifetime of energy infrastructure. Therefore energy system policies and direction need to be based on the best insights we can muster. Whatever their limitations are, energy models provide an essential tool to inform such insights.

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8 Refer to Lahdelma et al. [123] for an analysis of multi-criteria decision making processes of an electricity retailer considering uncertainties.

Part A
Integration Between Supply and Demand

'Smart Grids' are expected to help facilitate better integration of the entire electricity supply chain, from generation, storage, or transmission to the consumption of electricity. While the focus on the topic is increasing, only little discussion has occurred to date on how developing countries may benefit from advances in Smart Grids. Yet, some of the established and emerging concepts, systems and technologies grouped under the term Smart Grids may enable developing countries to leapfrog elements of traditional power systems and accelerate electrification efforts.

Correspondingly, a selection of Smart Grid options that could be implemented in sub-Saharan Africa is identified in Part A and a qualitative preliminary assessment of the potential of these options is made. The potential applicability of models as a tool for quantifying associated system benefits is one of the assessment criteria. Such quantification may provide valuable design and policy insights and help prioritise options. However, many existing energy system models rarely represent certain critical features associated with Smart Grids in a single comprehensive framework. Flexible and accessible tools like OSeMOSYS have the potential to fill this niche. Accordingly, the functionality of OSeMOSYS was enhanced to model elements of Smart Grids as part of this thesis research.

Section 1 explores what benefits Smart Grids could offer for sub-Saharan Africa. The notion of 'Just Grids' is introduced to reflect the need for power systems to contribute towards equitable and inclusive economic and social development without marginalising the poor. Specific Smart Grid options are identified and a qualitative assessment of the potential of these options is made. Section 2 describes how 'blocks of functionality' can be added to OSeMOSYS to better represent certain attributes of Smart Grids. These include variability in electricity generation, a prioritisation of demand types, demand shifting, and storage options. Through these enhancements OSeMOSYS may serve as a useful tool to quantify the potential of selected Smart Grid attributes to accelerate electrification in developing countries.

1 Smart and Just Grids for sub-Saharan Africa

1.1 Introduction

1.1.1 Rationale and Scope

According to the reference scenario in the World Energy Outlook [124], it is expected that Africa's electricity consumption will double between 2007 and 2030 from 505 to 1012 TWh. Over the same time period, the United Nations (UN) Secretary-General's Advisory Group on Energy and Climate Change (AGECC) has proposed that the UN System and Member States commit to ensuring universal access to reliable, affordable and sustainable modern energy services [125].

Specific elements of current and emerging Smart Grid concepts, systems and technologies might make an important contribution to achieving this goal by accelerating equitable and socially just[9] access to electricity services in sub-Saharan Africa. While this might include elements that are currently the centre of attention in industrialised countries, some options which explicitly address developing country needs might also emerge.

In this section, a concise description of the electricity sector in sub-Saharan Africa is provided. Further, a review of current Smart Grid concepts, technologies, benefits and initiatives is given. Section 1.2 of Part A of this thesis places the Smart Grids concept in the context of sub-Saharan Africa, highlighting the need to facilitate socially just access in order to avoid marginalising the poor. It then illustrates potential opportunities for leapfrogging elements of traditional power systems[10], mentions some

[9] According to Zajda, Majhanovich, and Rust [126], social justice generally refers to, "an egalitarian society that is based on the principles of equality and solidarity, that understands and values human rights, and that recognises the dignity of every human being".

[10] The terms electricity *infrastructure* or *power systems* encompass the entirety of the system, from generation, transmission and distribution to customer services and associated operations.

implications for network regulations and markets, and briefly discusses 'super grids'. Section 1.3 identifies selected Smart Grid options with a potential role in the near- to medium-term. Section 1.4 introduces and provides background on criteria by which these options might be assessed. The selected criteria include: consumers; operation & quality of supply; generation; environment; technical complexity; finance; human capacities; policy, regulation & standards; and the applicability of models. Based on these criteria, Section 1.5 provides an indicative assessment of the potential of the Smart Grid options. Section 1.6 suggests areas for further work to inform international cooperation, complementary to regional and national initiatives in sub-Saharan Africa. The potential role of Smart Grids to power sub-Saharan's grids is concisely summarised in Section 1.7. Explanatory remarks regarding the qualitative ranking are provided in Annex B.

1.1.2 Electricity in sub-Saharan Africa

In 2009, around 585 million people in sub-Saharan Africa (about 70% of the population) had no access to electricity services [127]. Unlike many other regions of the world, under current assumptions this figure is expected to rise significantly to about 652 million people by 2030. 85% of the people who lack access to electricity live in rural areas [128]. In addition to low energy access rates, the power sector is characterised by several other significant challenges including: electricity costs as high as USD 0.50/kWh, insufficient generation capacity to meet rapidly rising demand, and poor reliability of supply [129]. The estimated economic value of power outages in Africa amounts to as much as 2% of GDP, and 6-16% in lost turnover for enterprises [130].

In 2008, sub-Saharan Africa generated 380 TWh of electricity, of which South Africa alone produced almost 70% [131][11]. For a sense of scale, with 68,000 MW, the entire generation capacity of sub-Saharan Africa is no more than that of Spain[12]. Sub-Saharan Africa's average generation capacity was only about 100 MW per million inhabitants in 2009, ranging from less than 15 MW per million inhabitants in Guinea-Bissau and Togo, to 900 in South Africa, and up to 1,080 in the Seychelles [134]. By comparison, the generation capacity in

[11] Refer to Niez [132] for more details on South Africa's electricity sector and policies.

[12] Without South Africa, this capacity goes down to 28 GW, 25% of which is currently not available for generation due to, amongst others, ageing plants and lack of maintenance [133].

the EU is about 1,680 MW per million inhabitants, and it is 3,340 MW per million inhabitants in the U.S.

Fig. 4: Power pools in sub-Saharan Africa
[NEPAD 2008, as published by the IEA [135]][13]

The significant need for accelerated electrification rates has been widely recognised by regional (economic) communities[14] and is largely underpinned by national electrification policies. More than 75% of sub-Saharan countries have defined targets for electricity access [137]. In addition to regional economic communities and national governments, the main actors for implementing

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13 The difficulties in accessing the original source of this figure are representative for the overall time and effort required to access regional data and information on the status of electricity infrastructure in Africa. Typical transmission voltages used in Africa's grids are mentioned in ESMAP [136].

14 Such as: The Forum of Energy Ministers of Africa's (FEMA) Position Paper on Energy and the MDGs [137]; The Southern African Development Community's (SADC) Protocol on Energy [138] and its Regional Indicative Strategic Development Plan (RISDP) [139]; The Economic Community Of West African States' (ECOWAS) Energy Protocol [140] and its White Paper for a Regional Policy [141]; The Common Market for Eastern and Southern Africa's (COMESA) Energy Programme [142]; The East African Community's (EAC) Regional Strategy on Scaling-up Access to Modern Energy Services [143] and its Power Master Plan Study [144]; The Treaty Establishing the Economic Community of Central African States [145]; The Economic and Monetary Community of Central Africa's (CEMAC) Energy Action plan with energy and electricity access goals [137]; and the Africa-EU Energy Partnership [146,147].

electrification plans are the regional power pools and utilities. The power pools were established under the auspices of Regional Economic Communities to create competitive markets and improve the delivery of electricity services to customers [148]. They comprise the Southern, West, East and Central African Power Pools (the SAPP, WAPP, EAPP and CAPP, respectively) [135].

Fig. 4 provides an overview of the current transmission grid and extensions foreseen by the regional power pools and utilities. It is clear that sub-Saharan Africa's national grids are not well interconnected. While the importance of regional and national electrification initiatives is well understood at the policy level, the priority has to be to translate this understanding into provision of electricity services 'on the ground'.

1.1.3 A Smart Grid Approach

1.1.3.1 Defining the Term

The term 'Smart Grid' has come to encompass a range of innovative tools, technologies and practices envisioned to be supported by novel business models and regulatory frameworks. All of them ultimately should serve to help ensure a reliable, secure and economically efficient supply of electricity services. While there is consensus on this overall objective, the precise scope of the term Smart Grids is interpreted differently according to perspective and environment[15], and continues to evolve.

The Electric Power Research Institute (EPRI) [150] defines Smart Grid as, "a modernisation of the electricity delivery system so it monitors, protects and automatically optimises the operation of its interconnected elements – from the central and distributed generator through the high-voltage network and distribution system, to industrial users and building automation systems, to energy storage installations and to end-use consumers…and their devices". Zibelman [151] describes Smart Grids as an evolution of conventional grids by:

- Transitioning the grid from a mostly unidirectional radial distribution system to a multi-directional grid;

[15] For example, according to J. Antonoff, the U.S. focuses on technologies while the EU prioritises policies and strategies, assuming that technologies will follow [149].

- Converting from an electro-mechanical system to a primarily digital one; and by
- Moving to an interactive grid that actively involves end-users (or at least improves data availability and flexibility in meeting end-user demands)[16].

The European Technology Platform (ETP) outlined the notion of Smart Grids [153] through the following elements: optimising grid operation, use and infrastructure; integrating large-scale variable generation; information and communication technology; active distribution networks; and new market places, users and energy efficiency.

Much of the literature focuses on how Smart Grids could help establish a two-way flow of information between supplier and user to increase the efficiency of network operations [154–161]. Yet a common functional and technical definition has not emerged [162]. For our purposes, Smart Grids is a broad concept that covers the entire electricity supply chain and is characterised by the use of technologies to intelligently integrate the generation, transmission and consumption of electricity [163]. Thus, Smart Grids elements are part of a continuum of power sector tools and technologies.

1.1.3.2 Technologies

While Smart Grids are composed of complex and integrated systems, they often build on proven advanced technologies. Related technologies can generally be divided into those linked to physical power, data transport and control, and applications [157]. The National Energy Technology Laboratory (NETL) has identified and grouped many Smart Grid technology components [164,165]:

- Integrated communications[17], including Broadband over Power Line (BPL), digital wireless communications or hybrid fibre coax.
- Sensing and measurement, including advanced protection systems, wireless, intelligent system sensors for condition information on

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[16] Conventional grids usually provide detailed control at transmission level and good control at distribution level, but mostly do not go beyond that to control elements such as distributed energy sources or user appliances [152].

[17] Interoperability of equipment is a key requirement of Smart Grids.

grid assets and system status, and Advanced Metering Infrastructure (AMI).

- Advanced components, based on fundamental research and development, including Unified Power Flow Controllers (UPFC), Plug-in Hybrid Electric Vehicles and Direct Current micro-grids.
- Advanced control methods to ensure high quality supply, including advanced Supervisory Control and Data Acquisition (SCADA) systems, load and short-term weather forecasting, and distributed intelligent control systems for Smart Grids to become self-healing.
- Improved interfaces and decision support to reduce significant amounts of data to actionable information, including online transmission optimisation software, enhanced GIS mapping software and tools to increase situational awareness.

An alternative grouping of Smart Grid technology areas can be found in the 2010 Energy Technology Perspectives report by the IEA [166].

1.1.3.3 Benefits

Drawing on these groups of technologies, Smart Grids are expected to allow some level of dynamic balancing and optimisation of generation and delivery assets, and loads. Associated key technical benefits may include: improved reliability and resilience, cost-effective integration of variable resources and loads, increased efficiency of system operation, and optimised utilisation of both generation and grid infrastructure assets[18]. For example, through the facilitation of demand response measures, Smart Grids may allow shifting loads from peak to off-peak periods. This may help increase the utilisation of existing power plants and defer future investments in grid and generation capacities. Smart Grids may deliver these benefits at potentially lower overall cost than would be possible under business-as-usual assumptions.

Many of these potential Smart Grid benefits would be valid for sub-Saharan Africa, yet the concept and associated policies require refinement. Detailed assessments of the cost implications for utilities, consumers and society will be needed to justify specific investments [161].

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[18] Based largely on improved communication and increased interoperability at all grid levels [167].

1.1.3.4 Initiatives

In this regard, many countries are engaged in programmes and pilot projects to test Smart Grid concepts, for example: in Yokohama, Japan [168]; and Boulder, Colorado, U.S. [156]; the Jeju Island project in South Korea [169–172]; China's Strong and Smart Grid Roadmap [173], initiatives in Yangzhou, China [174]; the TWENTIES [175] and EcoGrid projects in the European Union [176,177]; and planned Smart Grid applications for Masdar City, United Arab Emirates [178][19]. While not much precedence seems to exist in Africa, South Africa launched the South African Smart Grid Initiative (SASGI) [181] and the Smart Grid technology company BPL Global has signed a 5-year contract with the national utility of Ghana [182].

Building on existing and anticipated experiences from such initiatives will help assess sub-Saharan Africa's potential to profit from Smart Grids. It will provide valuable input on how to refine existing concepts and associated policies to optimise their cost-benefit balance.

1.2 The sub-Saharan African Context

Employing a subset of envisioned Smart Grid advances may enable sub-Saharan African countries to leapfrog traditional power systems and ramp-up efforts to reach more effective solutions. This could accelerate national and regional electrification timeframes, while improving service and minimising costs and environmental impact. The term '*Just Grids*' is introduced to reflect the importance for power systems to contribute towards equitable and inclusive global economic and social development. Given the specific needs of sub-Saharan Africa, it is suggested that a Smart Grid approach for this region cannot simply be a copy of practices in industrialised countries – the starting point, challenges and opportunities are often too different.

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[19] For further information on pilot projects and policies refer to Doran et al. [160]. For a U.S. focus and information on dynamic pricing and pilot design principles refer to Faruqui et al. [179]. The consumer response to smart appliances combined with pricing signals was assessed in a project described by Chassin [180].

1.2.1 A New Emphasis

In this thesis, the concept of Smart and Just Grids for sub-Saharan Africa is broadly defined as one that embraces all measures in support of short-term and future integration of advanced two-way communication, automation and control technologies into local, national and regional electricity infrastructure. Accelerated access to electricity services may be facilitated through optimising grid systems, operations and technologies. This would allow for a potentially higher penetration of variable renewable energy sources and improvements to the reliability[20] *and economic efficiency of electricity supply. In addition to being smart, socially just power systems are required in sub-Saharan Africa in order to promote access to modern energy services without marginalising the poor*[21].

In the future, Smart and Just Grids in sub-Saharan Africa could provide similar functionality to Smart Grids in industrialised countries at full deployment, even though they may follow a different development pathway and timeframe. The diversity of the electrification status in sub-Saharan Africa[22] means that lessons learned from other regions may be directly applied in certain areas, while tailored solutions will be required for others. Constraints such as a lack of limited investment capital, largely inadequate institutional and physical infrastructure, and a gap in well-trained power sector personnel are likely stifling innovative practices that could already be occurring organically[23].

In order to realise the potential of Smart and Just Grids in sub-Saharan Africa, creating an enabling environment is therefore essential. Below some thoughts about elements of such an environment are presented, which may be addressed by policy makers, investors and other stakeholders.

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[20] Note that increases in variable renewable energy generation might require parallel investments in supportive infrastructure to maintain reliability requirements. Such investments could target storage options, the distribution and/or transmission grid, and generation and demand response options for the provision of reserve services [183].

[21] Similarly, UNEP [184] calls for a just transition to a sustainable, low-carbon economy to ensure that social aspects are equitably integrated into economic and environmental considerations, and that emerging opportunities are adequately shared among stakeholders.

[22] This diversity is comparable to India, which may offer a significant potential to learn from its Smart Grid developments. Refer to Balijepalli, Khaparde, and Gupta [152] and Balijepalli et al. [185] for a focus on India's related endeavours.

[23] For example, the electrification of New York started with Thomas Edison's effort to develop a successful business, covering the complete system of electric generation, distribution and appliances (the light bulb) [186,187].

Smart policies: Defining common ground rules for integrating technologies and business practices, identifying better ways to support effective demand-side management, and developing new policies to support the integration of distributed generation. All such policies would need to be underpinned by well-defined performance goals and transparent metrics to ensure effective monitoring of anticipated benefits.

Focus for sub-Saharan Africa: Leveraging international Smart Grid frameworks, legislation, regulation and standards, and adjusting them to the sub-Saharan African context[24] will be essential. New policies may need to diverge from international precedent, in order to respond to rapid demand growth and urbanisation, reduce theft of electricity and utility assets, and prioritise access to affordable electricity services[25] for the poor, supported by simplified requirements for rural electrification schemes. Such policies should enable access through flexible, no-regret electrification strategies that accommodate expansions of stand-alone systems, mini and national grids, and that support their integration.

Smart planning: Adjusting the grid to local circumstances and developing design principles that ensure an effective interoperability of existing and new grids, leading to even smarter networks over time.

Focus for sub-Saharan Africa: A balanced approach between regional grid integration, national grid enhancements and decentralised mini-grids is required. While smart mini-grids, such as those described by Katiraei and Iravani [189], may provide a short-term solution to rural electrification needs, their future integration into national and regional grids and *vice-versa* should be an integral consideration of power system planning[26].

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24 Refer to Schwartz [188] for further information on policy support required to deliver Smart Grid benefits.

25 This may even include a differentiation between individual services, ranked based on local priorities. For example hot water heating may be more 'interruptible' than say vaccine cooling in a clinic.

26 For example, in remote areas photovoltaic (PV) panels can provide a limited and thus at times limiting quantum of electricity for customers. At present, such customers are considered 'electrified'. In the case of mini- or national grid extensions with better power quality, such customers may either not be targeted or the photovoltaic system left unused, as current systems are often not designed to integrate such home circuits or local grids. A Smart Grid may help provide limited initial access followed by improved bulk service supplies as stand-alone systems are integrated locally and nationally.

Smart systems: Guaranteeing the security and quality of supply through smart automation and control arrangements, building on load management and integration of distributed energy sources, for mini, national and regional grids, for example as shown by Ruiz et al. [190][27].

Focus for sub-Saharan Africa: National and locally appropriate supply quality standards will need to be derived. These may initially be less stringent than current practices in industrialised countries and may vary by class of service. Increasing the grid's load factor through demand side management may also significantly help reduce costs, especially for rural electrification schemes [191]. Ultimately, a strong high voltage (HV) grid may be developed as a backbone of the power system, especially to foster electricity intensive industrial growth.

Smart technologies: Deploying proven smart technologies, optimising inter-operability with emerging technologies, and developing future solutions to best address electrification needs [192,193].

Focus for sub-Saharan Africa: The technology deployment path will vary widely at regional and country levels due to diverse needs and goals of different societies and markets. Defining these technology pathways and markets and verifying them through pilot projects will be important first steps.

Smart people[28]: Building stakeholder capacity[29] to facilitate the transition to Smart Grids, to operate the grids, and to attract and actively engage the private sector and consumers to maximise the number of people who profit from the transition to Smart Grids.

Focus for sub-Saharan Africa: Educating consumers in sub-Saharan Africa about efficient electricity use whilst moving towards Smart Grids will be essential, especially for those who previously had no access. Training tools and materials

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[27] This represents a shift from traditional preventive control philosophy to a corrective, 'just in time', control approach. Benefits include enhanced utilisation of grid assets and improved efficiency. Supportive new techniques and tools for system operation and design need to be developed and applied. For example, at industrial and institutional levels, under-frequency protective relays for heating, cooling and motor loads can provide significant support for grid operation.

[28] In this context, 'smart people' refers to energy-informed and hence empowered stakeholders.

[29] This includes policy makers, government agencies, regulators, electricity network and service companies, traders, generators, finance institutions, technology providers, researchers and users.

about state-of-the-art power systems will also need to be widely disseminated to analysts and technicians. Specific attention needs to be paid to the training of off-grid communities so they can manage and maintain mini-grid systems in a sustainable fashion.

Responsibility for ensuring that grids as a public good are smart and just falls mainly on governments and utilities. The following Just Grid characteristics are especially relevant to sub-Saharan Africa:

Just access: Ensuring universal access to electricity by:

- Encouraging electricity to be tapped-off from larger grid extension projects to local customers *en-route*. Connections for large consumers are often the primary driver for grid extensions. Such extensions may offer a great opportunity to connect the under-served at the same time[30];
- Using grid technologies that can cope with fluctuating supply and demand in rural areas and thus increase quality of supply, for example by building on strategic load control and management instead of conventional load shedding;
- Focusing on accelerated access to key electricity services rather than access to electricity in general. Doing this in a 'smart' way may help governments deliver on their development agendas more effectively and at lower cost, for example by prioritising electrical services required to specifically meet the Millennium Development Goals (MDGs) [195];
- Expanding service delivery under resource constraints by increasing the efficiency of electricity supply and use;
- Creating additional revenues for utilities through higher payment discipline enabled by advanced metering infrastructure, which might encourage utilities to extend services to new customers.

[30] Note that past electrification efforts in now highly developed countries followed a similar pattern [194].

<u>Smart and Just financing</u>: Developing a commercially successful business model encompassing pricing, cost structure and sales. Creating flexible tariff structures and payment schemes to ensure affordable and sustainable access to electricity services, by:

- Realising the potential of Smart Grids to help lower prices of electricity services by optimising the utilisation of grid assets, segmenting electricity markets according to reliability and quality requirements, minimising technical and non-technical losses by promoting smart and efficient appliances, and increasing cost-effective integration of renewable energy in remote areas[31];
- Providing additional support programmes to identify and foster productive uses of electricity to help ensure that low-income consumers can pay for their required electricity services;
- Allowing for targeted subsidies through integrated smart billing to support 'basic' services such as food refrigeration, as opposed to 'luxury' services, like television. Ensure subsidy schemes that are targeted towards the poor and provide incentives for utilities to expand access [198].

There is clearly a vast array of Smart Grid elements available to support this redefined concept. They are not all immediately relevant, however, and some are either not developed enough or at present prohibitively expensive to be usefully deployed in the sub-Saharan African context in the short- to medium-term. Avoiding technology lock-in will be crucial, as the economic lifetime of electric power equipment can be up to 50 years and longer [136,199].

[31] This may be especially beneficial when diesel power generators are used, as renewable energy may provide a cost-competitive alternative. This is because fuel transport costs to provide diesel to remote locations in developing countries may be significantly higher than in most industrialised countries [196]. For example, power prices in most Caribbean and Pacific Islands range from USD 0.06 – 0.60 per kWh [197].

1.2.2 Opportunities for Leapfrogging

The opportunity for Smart and Just Grids to leapfrog[32] traditional power systems may mean that they can offer even more promising opportunities to developing than to industrialised countries. While some components of Smart Grids offer a good basis for leapfrogging in the short-term, for others it will be essential to set the preconditions today which are required for enabling a transition to smarter networks as the technologies mature in the future[33].

In the short term, leapfrogging is envisioned to occur mainly for the components based on information and communication technologies (ICT), which form an integral part of many Smart Grid systems. In certain cases, Africa already notably 'leapfrogged' to more efficient ICT solutions. Although not a perfect analogy, the information revolution[34] of the mid-1990s in sub-Saharan Africa linked to the use of mobile phones offers some useful lessons.

Africa became the world's fastest growing cell phone market [203] with growth rates in the order of 300% per annum in countries like Kenya and Cameroon [204]. Within 10 years, the number of mobile phone subscriptions in sub-Saharan Africa shot up from four per 100 people to 53 in 2011 [205]. The actual number of users is expected to be much higher still, due to people sharing their mobile phones, especially in poor communities[35] [207,208].

One reason for the mobile sector's great success was the failure of conventional telecommunication systems to meet consumer demand, both in terms of number of connections and quality [202]. This constitutes a parallel to the failure of current electricity networks in sub-Saharan Africa to meet the needs of millions of Africans. Another reason for the rapid diffusion of mobile phones was the lack of red-tape involved in registering for the pre-paid services that are

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32 A definition of technology leapfrogging can be found in Davison et al. [200]. Examples of leapfrogging in developing countries in the field of energy are mentioned in Goldemberg [201].

33 For example, latest conductor technology and controls could be used for current greenfield developments to ensure long-term flexibility for integrating energy sources [166].

34 Wilson III and Wong [202] defined the information revolution as an institutional and policy revolution, highlighting the importance of private sector participation, foreign investment, competition and de-centralisation.

35 Grameenphone has 6 million subscriptions in Bangladesh, 3% of which are for 'village phones', which are shared by a large number of users, and account for one-third of the traffic [206].

used by 90% of mobile subscribers in sub-Saharan Africa [207][36]. Pre-paid subscriptions address especially the needs of people with lower or irregular incomes, as no bank account, mail address, or fixed monthly fee are required [209]. Smart and Just Grids could take advantage of ICT infrastructure to implement similar payment schemes.

In addition to technological reasons for leapfrogging, market models that accompanied the mobile phone revolution such as sharing phones may serve as a precedent for Smart Grids. Other success factors, which may not translate as seamlessly to Smart Grids, were the relatively low initial investments and the quick installation of re-deployable assets, making related initiatives less dependent on institutional frameworks and investor protection [210].

Mobile phones also offered large benefits at low costs to consumers which were already connected to conventional telephone networks, both in terms of flexible payment schemes and increased availability. Overall, there was a strong drive by consumers to make the mobile phone revolution happen and telecom companies found themselves in a profitable space.

This constitutes a major flaw in the analogy with Smart Grids. There, mainly utilities and governments are expected to be the driving force and effective market places still need to be developed. Further, apart from increased reliability in supply for existing consumers, especially those might benefit who gain accelerated access to electricity. This could be due to their connection to smart mini-grids or due to grid expansions facilitated by more efficient power systems.

1.2.3 Implications on Network Regulations and Markets

Present regulation often rewards utilities for delivering network primary assets rather than improving performance through more sophisticated management and advanced network technologies. Thus, regulation can hinder Smart Grid developments that do not focus on investments in network assets.

Most current network design and operation practices centre on the historic deterministic N-1 approach that was developed in the late 1950s [211]. A system which adheres to the N-1 rule maintains reliable operation even if a major

[36] Access rates are much higher than subscription rates, reaching almost 100% for some countries. This potential access is not directly beneficial for the large majority of the African people, who still cannot afford to pay for the services [207].

element fails, e.g., a transmission line. This rule exists in several variations depending on reliability requirements. It has broadly helped deliver secure and reliable electricity services, alongside various other traditionally applied redundancy measures.

These approaches can, however, impose major barriers for innovation in network operation and for the implementation of technically effective and economically efficient solutions that enhance the utilisation of grid assets[37]. For example, Divan and Johal [212] demonstrate significantly higher network capacity while meeting N-1 contingency constraints using distributed power flow control devices. Even higher utilisation is realised if the N-1 constraint is dropped. Yet, the existing network and its standards are commonly taken as granted in research work, thus constraining the applicability of diverging approaches [213]. Reforms seem overdue: in sub-Saharan Africa laws governing the power sector and at times over-sophisticated standards sometimes originate back from colonial times [191].

A relaxation of power quality and reliability standards based on the advances of Smart Grids may enable sub-Saharan Africa to profit from the associated significant cost savings potential[38]. Such a relaxation will help balancing asset- and performance-based options, particularly those that involve responsive demand and advanced network management techniques. In sub-Saharan Africa, novel regulatory regimes will also need to incentivise innovative ways of enhancing access to the grid.

Innovation is not only required in technologies and regulation, but also in designing power markets. Information systems infrastructure will help facilitate a shift to distributed control, with demand response becoming a key resource for delivering network flexibility and control. This will require significant changes in electricity market design principles, with a move away from traditional single-sided competition in large-scale generation.

Ultimately, a cost-effective system requires all market players to interact competitively to optimise demand and supply [214]. While markets based on these principles are still mostly conceptual, in time, it will be important to

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37 An overview of how standards can support or hamper Smart Grids developments is provided in EPRI [150].

38 Such an approach could be supported by a range of advanced technologies such as dynamic line rating, coordinated special protection schemes, coordinated corrective power flow and voltage control techniques (potentially supported by wide area monitoring, protection and control technologies), and application of advanced decision making tools.

develop more user-centric market models for sub-Saharan Africa. This approach will be critical for enhancing access to electricity services, especially given the benefits of a closer integration of consumers, such as enhanced asset utilisation and improved operational efficiency.

1.2.4 Smart Grids vs. Super Grids

Crucial benefits of electricity grids result from a diversification of both demand and supply. National distribution networks of several thousand households are usually large enough to profit from demand diversity and associated significant savings in supply capacity requirements [215][39]. Larger transmission networks are required to profit from diversification of supply by exploiting regional energy resources and infrastructure[40]. Transmission expansions can further significantly enhance the ability of the system to minimise fluctuations in demand and supply, increase the availability of back-up capacity [217], and minimise the required operating reserve. This is especially important when accommodating increased levels of variable renewable generation.

Critical voices like Sebitosi & Okou [204] however regard grand infrastructure plans to link up the African continent's power grids as obsolete in the age of Smart Grids. Some aspects of this view are mirrored in the U.S. by Cavanagh [218] and Fox-Penner [219], who emphasise the importance of focusing on regional and sub-regional grids[41].

Sebitosi & Okou [204] further suspect that super grids would "largely serve to extract untapped natural resources from the less developed to the more

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[39] The capacity of an electricity system supplying several thousand households is only about 10% of the total capacity that would be required if each individual household were to be self-sufficient and provide its own generation capacity. A further increase in the number of households however only results in minimal savings.

[40] For the Southern African region, Graeber [216] identified savings of USD 2 - 4 billion over 20 years, equalling 5% of total system costs, when optimising generation and transmission investments at a regional level. 60% of this savings potential can be attributed to lower operational costs.

[41] Cavanagh recommends that establishing a single interconnected 'national' grid in the U.S. should be less of a goal then upgrading the current three giant regional grids. Fox-Penner suggests subdividing regional grids into smaller grids building on direct-current lines to avoid cascading failures. However, the U.S. Department of Energy (DOE) [199] still expects high-capacity transmission corridors to form the backbone of the U.S. grid in 2030.

industrialised members". An example they cite comprises high voltage direct current (HVDC) lines to integrate renewable energy from North African countries into the European power system [156,220]. Such plans seem to be the main focus of current discussions on modern grid investments in Africa. It remains to be seen to what extent the underserved in Africa will profit from such initiatives.

1.3 Identifying Specific Options

In line with findings from the ETP SmartGrids [154], the implementation of Smart Grids for sub-Saharan Africa will, *inter alia*, require: a toolbox of proven technical solutions, harmonised regulatory and commercial frameworks, shared technical standards and protocols, and supportive ICT systems. It will be especially important to future-proof current grid infrastructure projects in a cost-effective way to ensure their compatibility with future plans to upgrade them to Smart Grids.

Particular elements of Smart and Just Grids could help offer tangible and direct benefits in the short- to medium-term, some of which are mentioned below. They comprise both elements which are currently focused on in industrialised countries as well as elements which might be of particular interest for developing countries. The options cover varying degrees of complexity and detail, from technical options like load control switches to rather conceptual suggestions like low-cost access tariffs. Options which are qualitatively assessed in the next section are shown in *<u>italic and underlined.</u>*

<u>Transmission and substation design</u>: Especially for longer transmission lines, the scale of technical losses can become considerable[42]. Smart Grids could help reduce such losses, for example with *<u>improved power lines and transformers</u>*, as well as by facilitating maintenance schemes [132]. Existing substation transformers can be a significant source of total grid losses, being responsible for up to 40% [221]. For example, superconducting fault current limiting transformers can help improve system performance and efficiency [222]. Deploying low-sag,

[42] For a sense of scale, Sebitosi and Okou [204] note that "the estimated amount of power that is lost during the delivery of 2000 MW from Cahora Bassa through the 1500 km line to South Africa is nearly equal to the entire consumption capacity of Mozambique, the host generating country".

high-temperature conductors and dynamic line rating can significantly increase the electric current carrying capacity.

Wide-area monitoring and control[43] could support the accurate information required for real-time decision making to respond better to disturbances within the system [221]. This will enhance utilisation of primary grid infrastructure and contribute to a more efficient system operation. Some of the required advanced transmission technologies[44] may target the more developed existing grids in sub-Saharan Africa, and may be disproportionate in areas with limited grid coverage. This is especially true since advanced monitoring and control requires integration throughout the transmission system, facilitated by sophisticated grid design techniques.

Distribution system design: While its benefits might be considerable, smartening the distribution system is significantly more challenging than improving the transmission networks [161]. *Distribution automation* technologies could help improve power systems by extending intelligent control [221]. For example, smart sensors and flexible and intelligent switches and interrupters at critical points on distribution circuits could minimise the extent of outages and increase the speed of restoration [224], while keeping cost increases at a minimum. Smart distribution technologies allowing for increased levels of distributed generation will be especially important for addressing rural electrification needs and minimise connection costs. The planning and design of these networks will require full horizon planning, i.e., a 20 year plus period. The development of these grids will be atypical, but existing work on distribution planning may provide a useful starting point [225].

Power theft often contributes significantly to overall system losses in developing countries[45], reducing the economic performance of utilities. High-voltage distribution lines can help prevent illegal connections and improve power

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43 This represents a shift from the application of traditional local-based control in existing power systems.

44 In addition to synchrophasors, wide-area monitoring and control could build on intelligent electronic devices such as protective relays, programmable controllers and stand-alone digital fault recorders. Examples of applications include coordinated Volt-Ampere Reactive (VAR) control solutions [223] and adaptive system islanding and resynchronisation [221].

45 For example, only around 33% of all electricity in India is billed, which is mainly attributed to theft and inefficient billing practices [226]. In addition to pure electricity theft, cable theft may constitute a significant problem. In various municipalities in South Africa, all-day street lighting is used as an early warning system, despite generation constraints [132].

quality and reliability [132]. Smart metering infrastructure can help reduce theft further, e.g., through remote meter reading [227] combined with an independent transformer-loading based validation process.

Smart mini- and micro-grids: Mini-, and especially micro-, grids with high shares of renewable energy are generally complex to implement, primarily because of fluctuating generation and a low load factor[46]. The task of maintaining adequate power quality becomes a challenge, for example due to spikes associated with the starting current of motor loads [229] or the need to provide some form of back-up power. Smart components could help cushion such effects and better balance the overall system, e.g., through integrating new demand side management options.

Costs of such systems may be further cut through the implementation of *DC micro-grids*, especially when combined with photovoltaic generation. While losses can be reduced through saving layers of DC/AC and AC/DC power conversion, the more expensive protective devices required for fault management and control, such as coordinated power converters, add complexity and outweigh some of the potential savings. Further, a potential future integration into AC grids requires consideration.

The smart integration of grids, from the micro- into the mini-grid and ultimately the national grid, will allow bringing together decentralised electrification with national electrification plans. As a result, there might be scope to reconsider future (grid-based) plant mixes. For example, cheap base load could be provided by the national grid, while the integrated decentralised grids could rather be geared towards contributing to the more expensive peak load, ultimately reducing the overall electricity price.

At the mini-grid level, this may include the *integration of existing distributed generators*, e.g., a diesel generator from a hospital, which is especially worth considering when expanding the grid to previously un-electrified areas. Such generators are characterised by being close and well-adjusted to their consumer loads, which are supposedly often much higher than average household demand in sub-Saharan Africa.

When applied for offsetting peak demand, they may allow owners to profit from cost reductions if combined with according pricing schemes. Utilities and

46 Casillas and Kammen [228] present energy conservation supply curves for measures regarding generation, metering and energy efficiency measures for a mini-grid in Nicaragua.

society will profit from the capacity increases, especially during peak demand; improved quality of supply through increased flexibility; increased system efficiency with improved load factors; potentially lower emissions due to the reduced need for spinning reserves; and enhanced network security and resilience to price spikes, supply shortages and outages [230]. The economics of such integration has shown potential. Portland General Electric (PGE) estimates that integrating the installed distributed generation base in Portland, Oregon, U.S., to offset peak power purchases could reduce the price per kWh by around 30% up to over 60% of the wholesale peak price[47] [230,231].

Demand side management: Demand side management options for large[48] consumer loads, like *load control switches* at industrial or institutional facilities, can contribute significantly to optimising the quality of energy supply and reducing load-shedding through allowing to cut off peak-demand. Load-shedding usually affects the poorest electricity consumers the most, as they have limited possibilities to compensate outages[49]. Radio-controlled interruptible institutional water heaters or water pumping systems constitute just two examples for such load control. The associated reduction of service quality if electricity is not available instantly requires some form of compensation by utilities, most likely in the form of special tariffs.

The available mature technologies and market approaches constitute advantages of targeting a limited number of large industrial consumer loads, as opposed to a large number of residential consumers [161]. Yet, the latter can have an important role in contributing to realising the benefits of Smart Grids, e.g., through *smart appliances*. For example, smart refrigerators that hold enough thermal storage to withstand interruptions or avoid power use during peak loads could be deployed. Again, the reduction of service quality, even if minor, requires some form of compensation by utilities. Supportive policies will need to ensure that consumers profit from the additional costs they might have to bear. Minimum efficiency standards could help reduce the electricity use by such

[47] In the U.S., 22% of the peak demand equalling 170 GW is available in the form of consumer backup generators. This includes generators of up to 60 MW, but 98% of them are smaller than 100 kW [230].

[48] Large compared with the total capacity of the grid.

[49] Those who can afford it might, e.g., use back-up generators when load-shedding occurs, and this is just in case the districts where they are living in are affected at all.

appliances. But first, a solid business case will have to be demonstrated before smart appliances become an attractive option for sub-Saharan Africa.

Smart Grids would further allow for a *prioritisation of loads* according to public importance, guaranteeing a higher security of supply for buildings such as hospitals rather than for enterprises or households. Its system-wide implementation requires utility control down to individual consumers facilitated by remotely controlled switches. A system-wide roll-out of such switches might not be justifiable. Selective load control could be an option which is easier to implement. A higher priority could be given to some selected loads while all remaining loads could have the same, but lower, priority. A simple implementation might be to install separate distribution lines for those few high-priority loads. Additional control devices would therefore only be required at selected sub-stations. This might help maximise the benefits while minimising costs.

Local charging stations: While rural electrification is a priority in many countries, it cannot be entirely equated with electricity access for the poor, as millions of people live near the grid but cannot afford a connection [232,233]. For these people, *local charging stations* ensure a minimum level of access to electricity services, for example, for charging lanterns or batteries. Especially when used for lighting, they may replace more expensive and environmentally harmful energy sources like paraffin[50]. Elaborating a successful business model[51] at these stations could further spawn local businesses and jobs, both directly related to the charging services as well as possibly through public on-site access to electric tools and equipment, e.g., grain mills or ICT facilities. Local charging stations usually generate their demand on-site. While experiences exist internationally (e.g., by UNIDO [234]), such stations were often implemented as stand-alone systems, without using their potential to help balance the system. If smartly integrated into local mini-grids, the storage capacity additions through batteries may further help contribute to increased power quality and reliability, by compensating short-term power flow and voltage fluctuations. The modular nature of local charging stations would allow targeted investments to test the

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50 Even more so when generation is based on renewable energy. According to UNIDO [234], 10 of their renewable energy based "Community Power Centres" would replace 1.5 million litres of diesel generation annually, offsetting some 5,000 tons of greenhouse gas emissions each year.

51 This model would need to cover the logistics of battery ownership, management and charging.

integration in mini-grids before larger roll-outs. Another possibility would be the introduction of electric bicycles for taxi services. These could be charged at stations during off-peak hours, combining income generation with demand side management[52].

Billing schemes: As many Smart Grid components build on ICT, they might profit from 'piggybacking' on future telecom service expansions, such as the provision of electricity consumption information via *mobile phone services* [237]. Charging prepaid consumption credits via mobile phones using scratch cards or comparable devices may help address the specific needs of the poor[53]. The required installation of at least a very basic form of smart meter will enable remote meter readings, which may reduce administrative costs related to meter readings and billing, and might help reduce theft[54]. Further, remote meter readings will help increase energy efficiency by reducing the vehicle usage associated with manual readings [224]. The current experience with mobile phone services in sub-Saharan Africa, e.g., for agricultural market information or financial transactions, suggests a solid business case for mobile phone companies, which have shown to possess the capacity to implement and manage such services[55].

Meter-based tariffs incentivise an efficient use of electricity, which could result in considerable load reduction[56]. A basic *time-of-use pricing* scheme at household level may easily be introduced in sub-Saharan Africa to help balance demand.

52 Due to strong policy support, China has 120 million electric bicycles on its roads [235], with 21 million bicycles being bought in 2008 alone, at prices typically below USD 300 [236]. By controlling their charging time they could become one element of a Smart Grid.

53 Botswana and other countries were already using pre-paid meters in the 1980s [238]. Refer to Niez [132] for information on the introduction of prepaid electricity meters under South Africa's Integrated National Electrification Programme.

54 This was reported as one of the reasons for Italy's initiative to fit smart meters in 85% of Italian homes [239]. The Italian utility Enel S.p.A. reports annual cost savings of EUR 500 million from their investments in the smart meter technologies, which were characterised by a very low payback period, allowing it to recoup the infrastructure investment in just four years [161].

55 Since its introduction in 2007, the Kenyan M-Pesa mobile phone banking service was used by 40% of all Kenyans to transfer over USD 3.7 billion all together [240]. It is worth noting that the average customer is not rural and poor, as some might assume.

56 In a mini-grid in Nicaragua, the abandonment of a flat-rate tariff after the installation of meters helped reduce the overall electricity load by 28% by encouraging a more conscious use of electricity, thus enabling the mini-grid to operate for longer [228].

For energy-intensive industries, *real-time pricing* may be considered. These billing schemes will incentivise consumers to shift their more expensive peak demand to off-peak hours, resulting in a higher system load factor and operation closer to the system optimum. Further, they will help remove hidden subsidies that sometimes burden smaller customers, who are charged more than their fair share [161].

In addition, *on-bill financing* of energy-efficient and potentially smart appliances[57] may be an important tool to help consumers overcome high upfront costs and ultimately reduce their energy bill. On-bill financing enables utility customers to pay for specific investments through their electricity bill. For example, the utility could distribute energy efficient compact fluorescent lamps and refinance them via a small surcharge on its monthly bills. This would enable the utility to recover its initial costs over the expected lifetime of the lamps[58]. Implementing this measure will require some policy support to incentivise the efficiency improvements and associated generation and income reductions for utilities.

Enabled by the introduction of smart meters, a Just Grid could further address the needs of the poor by ensuring reliable *low-cost access during off-peak hours*. Curtailed access would be provided during times of higher demand[59]. Loads requiring higher reliability throughout the day would need to pay a higher tariff for this privilege[60]. First illustrative energy system model runs for a rural supply scheme indicate that the potential for low-cost tariffs is significant, as a large share of off-peak demand might be delivered at half the price of the average generation cost [243]. Providing low-cost access might increase the interest of utilities to connect the poor, as this might become less costly or even profitable. Utilities would also profit from the increases in system flexibility and a more efficient system operation due to a higher off-peak demand, and consequently a higher system load factor. Further, this could also encourage people to adopt energy-efficient practices for peak times, either because of higher tariffs or dependency on batteries[61]. Through increasing electricity access, such tariffs

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57 In a mini-grid in Nicaragua, the introduction of compact fluorescent lights helped to cut demand by 17% [228].

58 Refer to Bell et al. [241] for further information on on-bill financing.

59 Such demand would come from loads that require higher reliability, such as industrial and commercial usage.

60 In the Indian context, it has been proposed to ensure a higher quality of electricity supply for customers who regularly pay their bills and lower quality for those who do not [242].

61 This has been observed with water supply schemes, where communities adjust their behaviour to access a critical but economical resource. People carry out water-intensive activities such as

might replace environmentally more harmfully produced energy services, e.g., firewood for water-heating.

Conceivably, the introduction of smart meters in combination with smart appliances would even allow delineating *tariffs by service*. Targeted subsidies for basic energy services, potentially combined with minimum energy efficiency requirements, could ensure that consumers can afford meeting some of their most pressing demands with cleaner energy sources. Higher subsidies could be applied up to a certain consumption threshold and could be linked to tariffs with lower requirements for the reliability of supply. As the consumer is being charged for the service rather than the electricity, on-bill financing could easily be used to add the life-cycle costs of the appliance to the electricity price in order to derive the actual service cost. This may enable a more economically rational basis for choosing appliances. While the technical requirements for the implementation of tariffs by service might be prohibitive in the near-term, this option might increase in attractiveness as the overall power system advances.

Information systems architecture: Once a smart power system with two-way flow of information and intelligent control is set up, *data management tools* could help utilities distil relevant information in a manageable and understandable format. *Diagnostic software* may further help monitor the health of grid assets, predict problems in power distribution, and initiate corrective action. The required architecture must ensure interoperability and enable a smooth transition from existing to future power systems [221]. Special attention to security issues will be required in countries with limited robust governance regimes. User-friendly interfaces, such as cell-phone billing and transparent metering, will be equally important to engage customers successfully.

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cleaning clothes during hours of supply, and shift activities that need less water such as cooking to times with limited supply.

1.4 Selected Assessment Criteria

The potential of the options shown in *italic and underlined* before were further qualitatively assessed against various criteria. These include their impact, their requirements, and the applicability of models as a basis for quantitative future assessments. Their largely positive impacts were assessed across the entire power system, sub-divided into the categories: "Consumers", "Quality of Supply", "Generation" and "Environment". The requirements of an option, which to some extent reflects the costs to society, were sub-divided into: "Technical Complexity", the scope of required "Investments" and "Human Capacities", and the need for enabling support through "Policy, Regulation & Standards". These categories are briefly introduced with reference to broadly anticipated Smart Grid benefits and challenges. A preliminary assessment of the selected options of Smart and Just Grids is then provided in the following section.

Consumers: A user-centric approach, often requiring active participation of educated end-users, is key to the uptake of many Smart Grid options [153]. Consumers are largely expected to profit from the suggested initiatives. It is anticipated that Smart Grids may potentially play an important role in extending access to electricity and addressing the specific needs of the poor[62]. Further, Smart Grids may help create new jobs[63]. However, some increases in system flexibility may also mean reductions in service quality, e.g., when electricity for an appliance is not instantly available due to remote "smart" scheduling.

Operation & Quality of Supply: Smart Grids may significantly contribute to reducing costs of grid congestion, power outages and power quality disturbances[64] through increasingly efficient automated operations [246]. Building on advances in equipment monitoring and diagnostics as well as supportive standards allows for more sophisticated asset management and operation, especially when combined with active management of consumer

62 Not least because of the positive effects of electrification in general on children's education and women's empowerment, as demonstrated for Indian villages by Millinger et al. [244].

63 McNamara [245] estimates that Smart Grid incentives worth USD 16 billion in the U.S. could trigger associated projects amounting to USD 64 billion. This would result in the direct creation of approximately 280,000 positions and the indirect creation of a substantially larger number of jobs.

64 In the U.S., these costs are estimated to be in the range of USD 25– 80 billion annually [159].

demand. Examples include weather-related operational security standards or improved system flexibility through increasing the reliability and quality of supply for consumers with high requirements, while providing less reliable and lower quality power at reduced costs for consumers with lower requirements [166][65]. This may enable the release of latent network capacity [161,247] and reduce the need for spinning reserve [199]. Additionally, technologies such as power flow control could have a significant impact on the effective utilisation of network capacity under normal and contingency conditions, especially once grids advance towards increased interconnection.

Generation: This category comprises the direct implications of utility-focused Smart Grids initiatives on overall generation and capacity requirements. Africa's average transmission and distribution losses of 11% are close to the global average of approximately 9%[66] [166,248]. However, including non-technical losses, many countries in sub-Saharan Africa are characterised by much higher system losses of up to 41% [249]. Higher technical losses are due to less efficient and poorly managed and maintained equipment [250]; higher non-technical losses can often be attributed to uncollected debt, tampered meters and inconsistencies in billing due to corrupt meter readers or illegal connections [132,152,227,242].

Smart Grid technologies could help minimise technical losses in transmission, for example by facilitating more effective reactive power compensation[67] and improved voltage control [224]. They could address distribution losses[68] through adaptive voltage control at substations and line drop compensation to maintain feeder voltages based on load [251]. Non-technical losses such as power theft could be partially addressed with the help of smart metering infrastructure

65 This would require utilities to prioritise the reliability of services dependent upon target group, such as emergency services, financial institutions, industries, consumers, and industry [160].

66 Ranges vary from, for example, 5% in Japan [248] and 6% in the U.S. [134] to 26% in India [166].

67 For example, DC-to-AC current-controlled inverters can both supply and absorb reactive power only and do not participate in resonances, as capacitors do [160].

68 Distribution losses usually account for the largest share of total power delivery losses [136]. In Europe, increasing the efficiency of distribution transformers by 0.33% would have reduced losses by more than 100 TWh in 2000 and would result in savings of 200 TWh in 2030 [250]. For a sense of scale, the electricity generation of Australia in 2009 was 232 TWh [134].

[239][69]. Active demand-side management by utilities could further help minimise the need for expensive electricity supply to satisfy peak demand [246]. The IEA [9,161] estimates that Smart Grids potentially enable a 13% to 24% reduction of projected peak demand increases between 2010 and 2050[70].

Environment: A transition towards Smart Grids on its own may not be the primary strategy for achieving ambitious energy and carbon targets. However, it may provide a significant contribution to related electricity sector targets [253]. On a global scale, it is estimated that direct and indirect benefits of Smart Grids offer the potential for yearly emission reductions of 0.9–2.2 Gt CO_2 per year by 2050 [166][71]. Expected direct benefits include reduced losses, accelerated deployment of energy efficiency programmes and direct feedback on energy usage. Indirect benefits include facilitation of electric vehicles[72] and greater integration of renewable energy. This is because Smart Grids provide risk mitigation mechanisms which potentially allow relaxing current reliability requirements without comprising the overall system reliability. Current grid requirements often constitute a strong disincentive to less predictable, but cleaner, electricity sources [224].

Technical Complexity: While Smart Grids are likely to be composed of complex and integrated systems, they often build on proven advanced technologies. Additionally, several promising technologies on the horizon may also form part of future grids, e.g., high temperature superconducting materials, advanced electric storage systems such as flow batteries or flywheels, and power electronics devices for AC-DC conversion [183,199]. In addition to the complexities associated with the technologies themselves, the requirements

[69] Monitoring of transformer loading and third party assessments of potential misuse will help tackle such power theft, which is often difficult to determine in developing countries as it can involve collusion with linesmen and meter readers. For example, in Rio de Janeiro the local utility Ampla was able to reduce its revenue losses from 53% to 1.6% of the electricity supplied. This was mainly due to remote monitoring and disconnections [252].

[70] Doran et al. [160] mentions a study which estimates that a 1% reduction in peak demand would translate to cost reductions of 4%, equalling billions of dollars at system level.

[71] According to EPRI [251], Smart Grids in the U.S. could potentially reduce 60 – 211 Mt CO_2 per year by 2030. This is equivalent to converting 14 - 50 million cars each year into zero-emission vehicles under a "business as usual" scenario.

[72] Shifting demand, for example through electric vehicles, may in fact increase CO_2 emissions in systems where base load is met with more CO_2 intensive generation than peak load [160].

regarding their integration into, and management within, the system need to be considered.

Financing: The scale of investment required to enhance today's grids to meet the demands of future power systems is considerable. However, the detailed monetary implications are not yet fully understood [166]. Based on the IEA's New Policies Scenario, total investment in transmission and distribution is expected to reach USD 278 billion for Africa over the period 2011 – 2035 [127][73,74]. 2.1% of these investments will be required for the integration of renewable energy sources. In addition to the investments in the New Policies Scenario, USD 390 billion (in year-2010 dollars) would be needed over the period 2010 – 2030 to achieve universal access to electricity by 2030. Almost all of this additional amount would be required in sub-Saharan Africa[75] and only one third of it is expected to target on-grid solutions.

While the additional costs for massively upgrading existing grids to Smart Grids might not be justifiable, the business case when investing in new infrastructure is considerably better. This offers significant opportunities for sub-Saharan Africa (refer to Fig. 4 in Section 1.1.2 of Part A for an indication of the grid infrastructure requirements). Yet, the capital and operating costs associated with communication networks of Smart Grids are high, especially as suppliers lack economies of scale and price-in delivery risk [252]. The benefits are more difficult to monetise than the costs and issue of on-going debate. In general, utilities are characterised as risk-averse and may be conservative in assessing their benefits[76]. Free-riding strategies might result in strategically delayed investments [256]. The situation gets further complicated as cost might occur in one, but benefits throughout many sectors of the power system[77]. This is not only an issue for utilities. It will as well need to be ensured that customers profit

73 Barriers to Smart Grid investments are listed in MEF [163].

74 According to the Brattle Group [254], the U.S. electric utility industry is expected to invest USD 1.5 - 2.0 trillion in infrastructure within the next 20 years. For comparison, the total asset value of the electricity sector in the U.S. is estimated to exceed USD 800 billion, with 30% in distribution and 10% in transmission facilities [199].

75 In East Africa alone, billions of dollars will be required for supply and transmission infrastructure over the next two decades [19].

76 Resulting decision making may be assessed drawing on prospect theory combined with multi-criteria acceptability analysis [255].

77 For example, in many cases the benefits of reduced line losses are considered as customer benefits [252].

from the costs they have to bear. Supportive financing schemes might be required to enable them to cover upfront investments. While the overall benefits of Smart Grid investments outweigh the costs according to the IEA [183], developing a business case becomes a challenge.

Human Capacities: Smart Grids redefine the roles of power sector stakeholders, from those at policy and institutional levels to power equipment manufacturers, ICT providers, generators and consumers. Developing the required human and institutional capacities to best respond to stakeholder needs and responsibilities[78] will be essential for their successful implementation, especially given the major role of institutions to ensure social justice [257]. According to the IEA [166], technical capacity has to be developed from a relatively low level in developing countries, lending further prioritisation to capacity-building initiatives. For some larger and individual interventions, e.g., at the transmission level, it might be most efficient to 'import' expertise at the design stage. This will however not be sustainable for on-going efforts like the daily grid operation or continuing grid extensions at the distribution level. Ensuring technical expertise at the utility level will therefore be key.

Policy, Regulation & Standards: Policy support will be essential to trigger the required investments in developing countries. They need to facilitate a balanced approach towards the sharing of costs, benefits and risks between key stakeholders [161]. They are as well required to protect consumers against the negative impacts associated with the collection of consumer data and remote disconnection [258]. For developing countries, they are essentially important to ensure the justness of electrification plans. This includes as well the just distribution of costs across consumer groups, as energy expenditures have been shown to have a disproportionately high impact on those with a lower income level [259].

Novel regulatory regimes will be needed, not least to incentivise innovative ways of enhancing access to the grid, but also to reward improved performance as opposed to only focusing on network infrastructure. The future grids required in sub-Saharan Africa may offer fertile ground for a radical departure from traditional regulation and grid design practices. A relaxation of power quality and reliability standards based on the advances of Smart Grids may enable sub-

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[78] A description of these needs and responsibilities can be found in ETP Smart Grids [154].

Saharan Africa to balance asset- and performance-based options[79] and profit from the associated significant cost savings potential. Standards are further required for equipment, data transport, interoperability and cyber security[80]. They could help promote supplier competition, accelerate innovation, expand the range of technological choices, facilitate interconnections and ultimately lower costs for consumers [161]. Their enforcement, notably regarding stringent logical (computer) security requirements, presents obstacles to all countries. It will however be even more challenging for countries without strong governance systems in place.

Modelling: Given the increase in complexity of energy planning through Smart and Just Grids, power system modelling increases in importance to inform multi-criteria decision making. The required expansion and adaptation of traditional approaches to energy planning and modelling needs to include a more active role for demand, linkages with storage, and the integration of mini-grids into plans for grid expansion. In addition to optimising electricity systems from a technical perspective, Just Grids need to be optimised from a development perspective. Ensuring services for marginalised and rural communities will often not be the most cost-effective solution. New constraints (or different objective functions) need to be added to expand traditional least-cost optimisation models accordingly (for applications refer to, e.g., Hiremath et al., Herran and Nakata, Pachauri, or Welsch [243,261–263]). Further, limited access to finance might require reflection in the models, e.g., by considering capital cost curves as implemented by Ekholm et al. [264].

Modelling the flexibility of demand is often only possible to a limited degree in current energy system models. It may require in-depth knowledge and modification of the source code, which in many cases limits such applications to a confined circle of experts. OSeMOSYS may provide analysts with a new route to inform energy planning in developing countries.

79 However, the long-term goal to guarantee a strong and reliable HV grid in Africa as a backbone to the power systems should be kept in mind.

80 Balijepalli, Khaparde, and Gupta [152] underline the need for open, performance-based standards to ensure modularity and interoperability. Basso and DeBlasio [260] present the status of IEEE standards on interoperability and interconnection.

1.5 Indicative Assessment

Based on the criteria of the previous section, Table 1 provides an indicative assessment. In a single framework, it compares selected Smart and Just Grids options which are currently focused on in industrialised countries as well as options explicitly targeting developing countries. A brief outline of these options can be found in Section 1.3 of Part A of this thesis, where they are highlighted in *italic and underlined*.

The assessment criteria are grouped according to the main categories, i.e., impact, requirements, and the applicability of models as a basis for quantitative future assessments. The qualitative ranking is provided by using "++", "+", "o", "-", and "--", with "++" referring to strong potential drivers for the deployment of specific options, "--" to very persuasive arguments against specific options, and "o" to categories which are neither drivers nor barriers[81]. As such, "++" in the category "Generation" may refer to significant reductions in peak demand and losses (as opposed to an increase in generation), or "--" in "Technical Complexity" to significant requirements regarding the complexity of the technologies with little existing experience in their implementation. Annex B provides a brief explanation of the rankings for each assessment criterion.

It is important to note that this qualitative assessment does not intend to, and cannot have, the character of a rough cost-benefit analysis. The individual circumstances essentially influence the impact of and requirements for the integration of specific elements of Smart and Just Grids.

[81] Barriers for developing Smart Grids in South Africa can be found in Bipath [265]. Challenges, drivers and priorities in developing countries are mentioned in Bhargava [266].

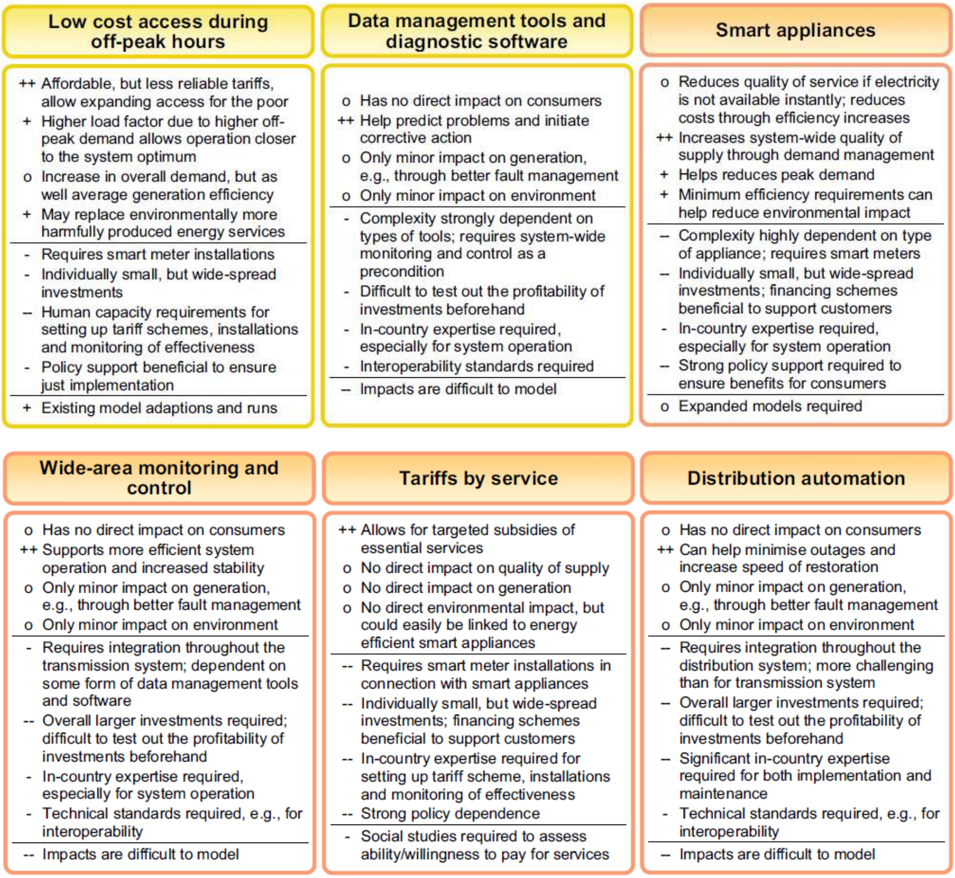
Table 1
Qualitative categorisation of selected Smart and Just Grid options

	Impact				Requirements				
	Consumers	Operation & Quality of Supply	Generation	Environment	Technical Complexity	Investments	Human Capacities	Policy, Regulation & Standards	Applicability of Models for pre-assessments
Local charging stations	++	+	o	+	+	+	+	+	o
On-bill financing	+	o	+	+	++	++	o	-	-
Mobile phone services	++	+	o	o	o	-	+	+	-
Load control switches	-	+	+	o	+	+	o	o	o
Integration of existing distributed generators	o	++	+	o	-	+	--	o	o
Prioritisation of loads	o	+	o	o	o	o	o	-	+
Improved power lines and transformers	o	+	++	++	-	--	-	-	o
DC micro grids	o	o	+	+	-	+	--	-	o
Time-of-use/Real time pricing	+	+	+	o	-	-	--	-	o
Low cost access during off-peak hours	++	+	o	+	-	-	--	-	+
Data management tools and diagnostic software	o	++	o	o	-	-	-	-	--
Smart appliances	o	++	+	+	--	--	-	--	o
Wide-area monitoring and control	o	++	o	o	-	--	-	-	--
Tariffs by service	++	o	o	o	--	--	--	--	-
Distribution automation	o	++	o	o	--	--	--	-	--

Table 2 describes the main characteristics of each selected Smart and Just Grids option in an individual box. Each box provides a concise statement for each assessment criteria, grouped according to the main categories, i.e., impact (Consumers/Operation & Quality of Supply/Generation/Environment), requirements (Technical Complexity/Investments/Human Capacities/Policy, Regulation & Standards), and the applicability of models as a basis for quantitative future assessments.

Table 2
Characteristics of selected Smart and Just Grid options

Local charging stations	On-bill financing	Mobile phone services
++ Expands access to those who can't afford connection; might help create jobs; can replace more expensive energy sources + Adds storage capacity to (mini-) grid o Demand increases may be covered with on-site generation + May replace environmentally more harmfully produced energy services + Existing experience, but not yet used to help balance the system + Targeted modular investments allow testing the concept + In-country expertise to be extended to enable better (mini-) grid integration + No specific policy interventions required o Expanded models required for pre-assessments	+ Reduction of upfront costs for energy- & cost-efficient (smart) appliances o No direct impact on quality of supply + Reduction of (peak) demand through efficient (smart) appliances + Reduction of associated environmental impact ++ Little technology requirements, besides of appliances themselves ++ Investments by utilities are directly passed on to consumers through bills o Some capacity building required to develop attractive financing schemes - Policy support beneficial, as such schemes might not be in the immediate interest of utilities - Social studies required for reflecting effects within demand-side models	++ Addresses especially the needs of those with lower or irregular incomes + Reduced costs for meter readings o No impact on generation o More energy efficient billing with slightly positive environmental impact o Existing experience with similar services, e.g., financial transactions; potentially good business case for phone companies - Requires smart meters - individually small, but wide-spread investments + Phone companies have capacities to manage such services + No specific policy interventions required - Social studies required for reflecting effects within demand-side models
Load control switches	**Integration of existing distributed generators**	**Prioritisation of loads**
- Reduces quality of service if electricity is not available instantly; compensation by utility required + Helps improve system-wide quality of supply and system stability + Reduction of peak demand possible o Environmental impact dependent on how peak demand is generated + Well known technologies can be integrated selectively for large loads + Targeted selected investments o Could be monitored centrally if only installed at large loads o Requires some regulation to specify degree of consumer flexibility and associated compensation by utility o Expanded models required for pre-assessments	o No direct impact on consumers, apart from profit for owners of generators ++ Improves quality of supply and system load factor + Helps utility to reduce its own peak generation o Environmental impact of diesel generation may be outweighed by reduced need for spinning reserve - Requires installing control automation for existing generators + Defers utility capacity investments – In-country expertise required for system design and operation o Requires some regulation to specify profit for owner from grid integration o Expanded models required for pre-assessments	o Effect on consumer dependent on consumer type and prioritisation + Improved security of access for high priority loads, e.g., hospitals, police o No impact on generation o No impact on environment o Selective load control possible; might require separate distribution lines o Type of investment strongly dependent on depth of system integration; targeted investments possible o Could be monitored centrally if only installed for selected loads - Policy decisions required to regulate prioritisation + Existing model adaptions and runs
Improved power lines and transformers	**DC micro grids**	**Time-of-use/Real time pricing**
o No direct impact on consumers + May improve system performance and efficiency ++ May significantly contribute to technical loss reduction ++ Improved transmission efficiency through loss reduction has positive environmental impact - Builds to a large degree on complex technologies -- Requires larger infrastructure investments - Foreign expertise could facilitate implementation - Development of technical standards required o Can indirectly be included in system models as costs and loss reductions	o Grid set-up has no direct influence on consumers o Only minor impact on grid operation + Loss reduction through saving layers of DC/AC & AC/DC power conversion + Improved transmission efficiency through loss reduction has positive environmental impact - More complex fault management and control increases complexity + Targeted investments allow testing the concept -- Expertise also required at local level to maintain the grid - Development of technical standards required o Can indirectly be included in system models as costs and loss reductions	+ Fairer, more cost-reflective prices eliminate hidden subsidies + Higher load factor allows operation closer to the system optimum + Reduces peak demand due to higher prices during peak hours o Environmental impact dependent on how peak demand is generated - Requires (smart) meter installations - Individually small, but wide-spread investments -- Human capacity requirements for setting up tariff schemes, installations and monitoring of effectiveness - Requires some regulation to ensure just tariff scheme o Expanded models required for pre-assessments



The categorisation in this section is guided by literature and largely based on its interpretation by the author of this thesis and the co-authors of the underlying journal paper [40]. The intention is to provide suggested direction for future initiatives, which would clearly vary to some extent when reassessed under specific on-the-ground conditions. A detailed and holistic assessment of the power sector will be a prerequisite in order to identify deployment pathways, which might ultimately turn out to contain a subset of the suggested options.

1.6 Further Work

Regardless of which specific aspects of the Smart and Just Grid concept for sub-Saharan Africa are pursued, international cooperation will be essential to realising its potential[82]. South–South cooperation could form an integral element of the required international action as many sub-Saharan African countries face challenges similar to those of developing and emerging economies such as India[83].

More specifically, Smart and Just Grids for sub-Saharan Africa can profit from coordinated efforts in the following selected areas:

Analysis of potential and roadmaps: Identify sub-Saharan Africa's potential to profit from Smart and Just Grids, including an assessment of associated costs and benefits. Based on electrification models, develop road maps for conditions which are common to many African countries, e.g., rural electrification, and support related efforts, for example by the IEA [161] or the scenarios developed for Africa by IRENA [267]. This includes the identification of technology solutions that could be rapidly and cost-effectively deployed in the short-term and would act as precursors towards long-term deployment pathways.

Country assessments: Provide international support for a preliminary assessment of the power sectors and as well the specific needs of individual consumer groups like households or industry. Based on this assessment, develop country-specific business and development cases for Smart and Just Grids. Prioritise investments in specific smart elements with clearly defined mechanisms for return on investment[84].

Power system design: Develop and deploy internationally supported open source or widely available modelling tools and capacities for power system design and operation, adjusted to the specific context. It is critically important

[82] According to Bipath [265], international cooperation for Smart Grids is expected to focus on standardisation, cybersecurity and interoperability.

[83] Balijepalli, Khaparde, and Gupta [152] report the detailed requirements and needs for Smart Grids in India.

[84] While the importance of business case development is emphasised, it needs to be recognised that many historical infrastructure projects were based on home-grown 'nation-building' initiatives.

that the system architecture developed enables future system upgrades without adding significant costs during early implementation stages.

Pilot projects: Implement joint pilot projects based on identified fast-track solutions. These pilot projects will help understand stakeholder behaviour within their redefined roles and allow testing the markets before engaging in massive rollouts. Remote rural electrification schemes with higher penetration rates of renewable energy sources might serve as a particularly good starting point.

Enabling environments: Help promote supportive policy, regulatory, institutional, legal and commercial frameworks. Sub-Saharan Africa could especially profit from ongoing efforts in industrialised countries to adjust related network standards. Additionally, legislation precedents could be employed to help reduce electricity theft[85]. Further, international design competitions could help highlighting challenges and develop innovative solutions.

Capacity-building initiatives: Train key stakeholders based on skills assessments. Developing the asset management capacities of African utilities and energy entrepreneurs to maintain technical systems and equipment will be vital for ensuring the sustainable deployment of Smart and Just Grids.

Financing: Identify a range of financing sources, from donor grants to private sector loans, and map their potential role in supporting different Smart Grids options. These financing sources should target interventions covering both, power system upgrades and expansions, including mini- and micro-grid solutions. Appropriate support instruments should be developed which address the financing needs of different stakeholder groups. Reliable investment environments will be required which enable a fair way of sharing risks, costs and especially benefits.

For a successful transition towards smart and just energy systems, international cooperation will need to be complemented by close engagement with regional and national stakeholders. While Smart and Just Grids require strong public commitment, including funding, the private sector as the main engine of

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[85] China's major reform of the rural power management system in 1988, combined with rural grid enhancements, helped reduce losses in low-voltage grids by 30 - 45% and consequently lowered electricity prices. Refer to Niez [132] for further information. For another example, refer to India's 2003 Electricity Act, which heavily penalises electricity theft [132].

economic growth has an essential role in supporting related initiatives in sub-Saharan Africa. A close integration of the private sector in related efforts will be key.

1.7 Conclusion

Sub-Saharan Africa is characterised by significant electricity-related challenges in terms of resources, infrastructure, cost and sustainability. Finding ways of enhancing future power systems represents a key task for governments, regional power pool authorities and national utilities. Some Smart Grid approaches may enable sub-Saharan Africa to leapfrog traditional power systems practices in the short term. Others will require preconditions to be established today in order to avoid technology lock-in and ensure compatibility with future concepts and technologies. Further research will be essential in narrowing down these preconditions to ensure the successful implementation of elements of Smart and Just Grids.

From an economic perspective, reliable energy supply through Smart and Just Grids will help foster economic growth. From an environmental perspective, Smart Grids will allow for a more efficient use of resources with lower associated greenhouse gas emissions. Most importantly, from a societal perspective, electrification is closely linked to many aspects of the development agenda. Therefore, accelerating electricity access by taking advantage of the opportunities offered by Smart Grid may speed up development efforts.

The significant electricity infrastructure requirements in sub-Saharan Africa offer a unique opportunity to learn from the most developed power systems and move forward without necessarily repeating all of their previous development stages. We should take advantage of this significant opportunity to ensure that sub-Saharan Africa's future grid is designed in a way that is both smart and just. Modelling elements of Smart Grids to identify their potential contribution may be a useful first step before piloting their implementation.

2 Modelling Elements of Smart Grids

2.1 Introduction

2.1.1 Rationale and Scope

Smart Grids may be composed of a suite of approaches, tools and technologies. Selecting the most appropriate options requires informed choices based on multi-criteria decision making. Energy modelling has a long history of providing support for such decision making by helping to characterise related energy policies and strategies (refer to, for example, Huntington et al. [20], Rath-Nagel and Stocks [21], Jebaraj and Iniyan [22], the IAEA [86], Meier [268], Häfele et al. [269], and Baker et al. [270]).

Commercially available analytical tools have developed organically over decades, gaining in maturity along with complexity. With the emergence of some popular families of modelling tools[86] and supportive capacity building (e.g., by the IAEA, ETSAP, IEA, or IIASA [274–278]), an increasingly wide audience has learned to apply such tools. Only a small subset of energy modellers is required to understand the details of the underlying code and adapt it to meet their modelling needs. This is, however, a prerequisite when aiming to test novel concepts before they are integrated into off-the-shelf software.

While many aspects of modern energy systems have been modelled using a range of existing tools, a comprehensive[87] and openly available modelling framework to assess Smart Grid solutions at an energy systems level has not yet emerged. Examples of related efforts include the modelling of high penetration of renewable energy [81,279] enabled by Smart Grids [35], storage options to balance variable electricity generation [280], market assessments of Smart Grid approaches with the Electricity Market Complex Adaptive System (EMCAS) [36], the impacts of smart appliances on household demand [37], and the modelling of demand side management (DSM) policies based on assumptions regarding future technology efficiencies and their market penetration rates [38].

[86] For example, tools such as MESSAGE, TIMES and MARKAL are derived from the Häfele-Manne approach [271] and often used for 'multi-regional' models. WASP, amongst others, constitutes a model that is frequently applied in Africa [272,273].

[87] Including the ability to model high penetrations of variable electricity generation and its implications on grid stability and reliability; storage; demand side management and load control; spinning, supplementary and standby reserve; etc.

In addition, stability and reliability analysis may help address the increasingly complex dynamic management of voltage and frequency control, especially in view of the growing integration of variable renewable electricity [281–283]. Smart Grids may offer significant opportunities for expanding access to modern energy services in developing countries. Yet marginalised and rural communities might not be prioritised, often due to the lack of a solid business case for utilities or limited public finance. In order to simultaneously characterise the potential of Smart Grids to electrify poor communities and quantify the associated system-wide effects, extended least-cost optimisation models may provide valuable support to the development of an improved business case. They may further help to gain insights on more targeted public finance to accelerate electrification efforts. Yet, broadly applied medium- to long-term optimisation models like MESSAGE, TIMES and LEAP only provide limited functionality with regard to Smart Grids.

For example, they do not enable a representation of the interactions of smart power system components with different electricity markets[88] and associated operational strategies as described for simulation models with a shorter time horizon by Lund et al. [284] and Andersen and Lund [285]. This is because the different prices within different electricity markets at the same time cannot be exogenously defined. Rather, these models endogenously derive one single price, based on exogenously defined resource prices and energy service demands, assuming an economically optimised dispatch at the system level[89]. Further, related grid stabilisation requirements as presented by Lund [287] and Hong et al. [288] are traditionally not considered in medium- to long-term energy system models, even though generic methods for their simple representation exist[90].

While short-term models are best suited to analyse the interrelations of Smart Grids with electricity markets, medium- to long-term models help assess their impacts on capacity expansions plans. Enhancing the representation of the relevant key dynamics for such expansion planning in the model code requires in-depth experience, which is usually only available to a limited group of experts.

88 For example, day-ahead, intra-day or reserve markets.

89 However, market splitting due to bottlenecks in transmission systems as considered in work by Lund [286] can usually be modelled by setting up multi-region models with transmission capacity constraints. The actual market prices within the regions then drives the regional capacity investments as well as investments in the transmission system between the regions.

90 A generic way to model this in most medium- to long-term models would be to define a 'dummy fuel' for the reserve services and assign power plants to produce this fuel in parallel to electricity [289]. Elements of Part B of this thesis build on this approach.

Flexible, transparent and open tools may therefore be increasingly useful to test out new hypotheses and approaches.

Accordingly, an OSeMOSYS model is extended to be able to assess the potential implications of selected Smart Grid options on power systems. Specifically, Section 2 of Part A of this thesis focuses on modelling the ability of Smart Grids to enable increased demand response and help facilitate the integration of non-dispatchable generation combined with storage options [161]. First, it is briefly described how OSeMOSYS is extended. Section 2.2 provides a conceptual description of the individual code additions. This is followed by the algebraic formulation in Section 2.3. An application is presented in Section 2.4 and concluding remarks in Section 2.5. The modified code itself is provided in Annex C.

2.1.2 Extending OSeMOSYS

OSeMOSYS serves as a useful and transparent tool to inform energy planning, as it easily allows the testing of new applications and formulations. First, it builds on an open source programming language and solver and therefore requires no upfront financial expenditures. Further, the code is relatively straightforward and well documented. The addition of new elements therefore only requires a relatively modest time commitment. Refer to Section 5.1 of the introduction of this thesis for further background on OSeMOSYS.

In Section 2 of Part A of this thesis, the existing OSeMOSYS code is extended to represent specific Smart Grid options. These include variable electricity generation, a prioritisation of demand types, shifting demand, and storage devices. These 'functional blocks' are sorted by increasing complexity. This familiarises the reader with simple code additions before proceeding to more complex modifications.

Given the multiple levels of abstraction used to describe these code additions, they can also be added into other models using a mathematical programming language such as GAMS (General Algebraic Modelling System) [290]. This requires the mathematical formulation to be translated into the specific programme language, and additional modifications to integrate it into the fabric of such models and ultimately into their objective functions. However, the descriptions of these code additions may also be useful for those using models where changes to the underlying code are complex to implement[91]. For example, the description of the storage block provides a conceptual understanding of a model element, which might otherwise be applied as a black box if embedded in a more complex model.

2.2 Conceptual description

This section outlines the main principles of the code additions and provides a 'higher-level guide' to the detailed algebraic formulation presented and explained in Section 2.3 of Part A of this thesis. In this section, cross references are employed which are indicated by bracketed labels. These refer to the detailed algebraic formulations. They further help identify the corresponding lines of the final code as presented in Annex C, where they appear at the beginning of each constraint.

The temporal resolution in OSeMOSYS is defined by consecutive years modelled, which are themselves split up into so-called 'time slices'. Each of them combines a fraction of the year with specific load and supply characteristics. One time slice could, for example, represent all the weekend evenings in summer, another one the weekday evenings in winter. As such, the time slices have no inherent chronology. This is a main difference to a short-term model like EnergyPLAN, which is run chronologically at a higher time resolution of hourly intervals [84]. While some information is lost through the definition of time slices, for the core code of OSeMOSYS such a temporal aggregation is preferable: the computational requirements can be significantly reduced and data entry simplified, especially considering the focus on long-term capacity planning. However, chronological information is required when modelling storage levels or when shifting flexible demand.

Apart from the modelling of 'Variability in Generation' as described in the next chapter, conversion factors are therefore used in the subsequent additions to attribute each time slice to a specific season, day-type and 'daily time bracket'. Seasons occur within a year, and day-types within a week, e.g., weekdays and

91 Examples may include the popular MESSAGE [80,114], TIMES [73] or MARKAL [106] models.

weekends. Daily time brackets refer to a defined timespan within one day, e.g., one hour, or mornings, afternoons and evenings[92].

2.2.1 Variability in Generation

The integration of variable renewable energy is a strong driver for the deployment of Smart Grids [154]. OSeMOSYS in its version as of 8 November 2011 did not allow for the analysis of variable, non-dispatchable electricity generation. Expanding the model to do so required minor modifications. One way to do this is to alter the capacity factor[93] parameter by increasing its temporal resolution from years to time slices. This provides the modeller with the flexibility to specify which technology is available and at what level throughout the year, for example, to constrain the night time output of solar panels as opposed to entering one average load factor for the entire year[94]. In this case, enhancing the functionality of OSeMOSYS is as simple as adjusting the two equations of the core code in which the capacity factor parameter appears (CAa4 & CAb1)[95].

2.2.2 Prioritising Demand Types

Smart Grids may contribute towards optimised system operation, for example, by ensuring near perfect reliability and quality of supply for high priority demand types, while reducing the requirements for demand types which are less sensitive to these needs [166]. This is especially relevant with regard to the management of power outages, or load shedding [291]. Loads may be prioritised according to demand types such as emergency services, financial institutions, industries, and consumers [160].

In order to enable a prioritisation of demand types, the model is extended to allow for leaving some demand unmet should the cost of supplying this demand exceed a predefined cost. This cost is commonly referred to as value of lost load

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92 For consistency, this new time resolution is also applied for the 'Prioritising Demand Types' addition, even though not explicitly required.

93 The ratio of maximum available capacity to design capacity.

94 Note that this functionality is already included in tools such as MESSAGE and TIMES.

95 Denominations as in the core code.

(VoLL) [292,293], or the cost of unserved energy (CUE) [294]. It could be interpreted as a measure of the resulting economic loss incurred by the customers, or indicate the cost below which it would be cheaper either not to meet demand, or meet it by other means such as with private backup generators or different fuel sources.

Several demand types can be entered with different degrees of flexibility and priority, i.e., shares of the loads which may remain unmet and prices per unit of energy demand which is not met. A demand type is entered as an overall daily demand with a specific demand profile, defined for each day-type, season and year. First, the rate of a demand is calculated for each time slice (D3). Within the core code of OSeMOSYS, a rate refers to an *amount* of electricity *per timespan*. The unit of a rate of a demand might therefore conveniently be chosen as kilo-, mega- or gigawatt. The rate of the unmet demand is then constrained to be smaller than a predefined share of the rate of demand (UD1). Next, the unmet demand within each time slice (UD2) and throughout the year (UD3) is derived. The yearly costs for not meeting a demand are calculated (UD4) and discounted to the beginning of the first year of the modelling period (UD5).

In order to integrate this prioritisation into the core code of OSeMOSYS, the rate of demand is split up into an inflexible 'standard demand' which has to be met whenever it occurs and flexible demand types which may be prioritised (D1a). The standard demand is calculated analogously to the flexible demand (EQ-rev = D2). Next, the costs for not meeting a demand need to be integrated into the objective function, which minimises the total discounted costs. In the core code, these total discounted costs were limited to technology related costs. The reference to technologies is removed from the total discounted costs (OBJ_rev, Acc4_rev) in order to be able to include costs related to not meeting a demand (TDC2a). The discounted costs which relate specifically to technologies are now renamed to differentiate them from costs related to not meeting a demand (TDC1_rev). With this final step, the prioritisation is an integral part of the OSeMOSYS code.

2.2.3 Demand Shifting

Smart Grids may further enable more efficient asset utilisation by decoupling growth in generation from peak load growth by shifting peak load to off-peak times [9]. About half of private household demand is estimated to provide this flexibility [295], such as dishwashing, washing of clothes, air conditioning and heating. In the transport sector, electric vehicles may provide this flexibility

[296]. In industry, related examples include electric boilers or process heat requirements. At a municipal level, pumps linked to water supply reservoirs can be called on.

While heat pumps or hydrogen production for vehicles[96] serve as flexible demand types, a demand within OSeMOSYS generally refers to a final consumer demand, e.g., electricity or vehicle-kilometres. A system with a heat pump would therefore not be modelled as a flexible demand, but as a technology with electricity as an input fuel and heat and cold as two output fuels to meet some potentially flexible demand. Similarly, hydrogen fuel cell cars could be modelled as one technology consuming electricity and producing hydrogen, and another technology representing the fuel cell car, which consumes hydrogen to meet a demand for vehicle-kilometres. Both technologies would be linked to the same storage device. Several vehicle types consuming different fuel types like hydrogen, ethanol or electricity could then 'compete' for one demand for vehicle-kilometres. Some flexibility could then be added to this final demand, if required by the analyst.

The main value added of the expansion of OSeMOSYS presented in this chapter is its user friendliness, as it allows modelling flexible demand in a straightforward manner with a couple of input parameters rather than through additional equations, as is the case in some other medium- to long-term energy system models [298]. The analyst can define the maximum timespan within which a final demand can be met earlier or later within a day. Further, a cost can be defined for each timespan that a demand is shifted. Such a cost could represent an 'inconvenience cost' a utility might offer to pay their customers in order to compensate their flexibility. Alternatively, such a cost could relate to 'storage' losses, for example when heating up a building earlier as needed. Additional investments might be required to facilitate this flexibility while minimising a reduction in quality of service for customers. Such investments may be due to required smart switches and appliances and can easily be added in the technology definition within OSeMOSYS.

In order to simulate demand shifting, the model is extended to allow demand to be met in advance or delayed within a given day. A 'storage' ability of an appliance is assumed, which can 'store' demand[97] for some time. The storage is

[96] Refer to Hake et al. [297] for an elaboration of the role hydrogen might play in future energy systems.

[97] As opposed to energy.

charged when the original demand is reduced[98]. The storage is discharged when this shifted demand is met, leading to an increase over the original demand at that time. Several flexible demand types can be entered with different degrees of flexibility, i.e., shares which may be shifted and timespans within which they have to be met, both for advanced and delayed loads. For each flexible demand, a cost per amount of energy and timespan shifted needs to be defined. If invoked, this cost also ensures that demand is only shifted as little as necessary for the purpose of reducing overall system costs.

Similar to the prioritisation of demand types, a rate of a flexible demand is calculated (D3), i.e., an *amount* of energy *per timespan* which is characterised by some degree of flexibility. The actual shifted demand is then constrained to be smaller than the predefined share of the flexible demand (DS4). The charging of the storage for the shifted demand is calculated separately for loads which are delayed (DS2) and loads which are met earlier (DS3). Both are added to obtain the overall charge (DS1).

The delayed loads are then constrained in several ways: (DS5) ensures that all delayed loads are ultimately met within a day; (DS6) ensures that within a day loads are first reduced before these reduced loads are then met at a later stage; and (DS7) ensures that they are met within the predefined delay. Loads which are met earlier are calculated analogously through the equations (DS8 – DS10).

Next, each shifted load is multiplied by the time it is shifted (DS11 & DS12). The costs of shifting demand are then obtained through multiplication with the cost for shifting a demand by one hour (DS13). These costs are then discounted to the start year of the modelling period (DS14).

Demand shifting is integrated into the core code in a very similar fashion as the prioritisation of demand types through the equations (D1b, EQ_rev = D2, OBJ_rev, Acc4_rev, TDC1_rev & TDC2b). They ensure that the overall demand is adjusted to include flexible demand types and that the costs for shifting a demand are minimised as part of the objective function.

98 Consider as an example a refrigerator which stops cooling when power is expensive, drawing on its 'cold storage inertia' to meet its cooling needs at a later or earlier stage, but at a lower cost.

2.2.4 Storage

As renewable electricity portfolios expand in many countries, the importance of gaining a better understanding of storage options is increasing [299]. System planners not only need to optimise the overall storage capacity, but also the mix of different technologies, from bulk to distributed storage, and from electricity to fuel and heat storage [300].

The methodology to model storage is straightforward. The model allows either storing or discharging energy during a time slice as long as storage levels remain within their prescribed minimum and maximum values. If these storage boundaries don't suffice, the model will investigate if new storage capacities should be added at a given cost of investment per unit of storage capacity.

In contrast to an hourly model like EnergyPLAN [301], storage calculations in medium- to long-term models are strongly characterised by the time slices the analyst chooses. Time slices represent fractions of the year with a specific load characteristic, for example, morning hours of weekdays in autumn. All model input parameters are defined as being constant within each time slice. Therefore, during each day within a specific day-type and each week within a season, exactly the same conditions for all generation and demand prevail. Charging and discharging patterns are consequently identical during such periods and repeat themselves until a new day-type or a new season starts.

As illustrated with dashed circles and capital letters in Fig. 5, extreme values can therefore only occur during the first and last week of a specific season, and during the first and last occurrence of a specific day-type. In order to avoid having to analyse if storage levels are within their boundaries at every instant throughout the year, only these times where extreme values may occur are assessed. This is done by adding up all energy charged and discharged throughout the modelling period up to this point.

For example, in Fig. 5, weekdays and weekends are the only two day-types defined within a season. The storage content is lower on Monday evening than on Monday morning of the first week in this season. Therefore, the storage levels have to be even lower on the Friday of this first week, as storage patterns are repeated during one day-type. Weekdays in-between do consequently not require any consideration with regard to their storage levels. Further, the storage levels are lower on Sunday evening than on Monday evening of the first week. Considering that also the overall weekly patterns are repeated within one season, they have to be even lower on the last Sunday in this season. Consequently, the storage levels of the last Sunday within the first week do not need to be assessed, and neither do the storage levels in the weeks in-between.

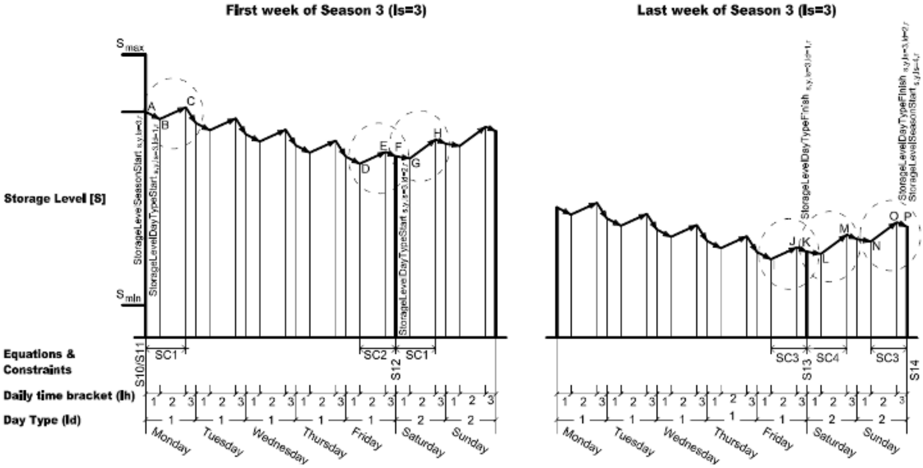

Fig. 5: Storage levels in the first and last week of a season

The capital letters [A] – [P], equations (S10 – S14), constraints (SC1 – SC4) and vertically aligned variables are cross referenced to text within this section and the algebraic formulation (refer as well to the online supplement). The storage boundaries are assessed for those levels which are referred to by capital letters.

The accuracy of the storage calculations – and the model in general – is strongly dependent on the careful definition of time slices by the analyst. In general, an increased number of time slices will lead to an increased accuracy, but at the cost of a more complex model, both with regard to data handling and computational performance requirements. Should more detailed insights into yearly storage operations and strategies be required, an hourly model as described and applied by Connolly et al. [302] might be preferable to a medium- to long-term investment optimisation model like OSeMOSYS.

Storage is implemented in OSeMOSYS in a similar fashion as in other models such as MESSAGE, TIMES or MARKAL. For simplicity, several potential characteristics of storage options are not taken into account. For example, when considering a hydropower plant connected to a reservoir, such characteristics could include evaporation and a dependency of the electrical output on the reservoir water level.

When considering battery storage systems, such characteristics could include a dependency of the battery lifetime on the depth of discharge, or of the storage capacity on the rate of discharge, i.e., the amount of energy which is withdrawn within a certain timespan. This is for example considered in other modelling tools such as HOMER [303]. When 'vehicle-to-grid' (V2G) storage should be modelled, such characteristics would include the availability of the maximum storage capacity as a function of the day time. When modelling heat storage, such characteristics include heat transfer, for example as modelled by Fitzgerald et al. [304]. Most of the outlined characteristics can easily be added to the model as needed, as long as the algebraic formulation complies with the requirements of linear optimisation.

A storage facility can be charged during the operation of one or more technologies in a specified mode of operation and discharged in another mode[99]. Allowing to link more than one technology to a storage option enables the modelling of a variety of technical options and management practices. For example, a simplified representation of compressed air energy storage (CAES) with constant isentropic efficiencies could be modelled by defining a technology which uses electricity to store air, while another technology produces electricity by withdrawing air and consuming natural gas. This would also allow modelling a simultaneous operation of compressor and expander when electricity prices are high [305].

Further, a pumped storage hydropower plant could be modelled as a technology linked to a reservoir. This technology would store energy with associated pumping efficiencies in one mode of operation, while withdrawing energy with associated turbine efficiencies in another mode of operation. A second technology could be added to represent water withdrawals for irrigation purposes, reducing the stored energy available for electricity generation. As such, at least a basic representation of the water, energy and food security nexus as described in Part C can easily be implemented in OSeMOSYS. In the following, the storage calculations are explained in more detail.

The storage charges are constrained to be within a predefined minimum and maximum rate (SC5 & SC6). Multiplying the rate of activity of a technology with the efficiencies of storing or discharging energy with this technology will give the actual charge or discharge rate[100] (S1 & S2). The parameters to describe

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99 Consider for example a pumped storage hydropower plant. When the power plant is operating in discharge mode, the rate at which the storage level drops is a function of the generated electricity. If there is more than one turbine discharging water the cumulative effect of all turbines is used to calculate the storage discharge.

100 Note that the rate of storage charge or discharge is a function of the technologies linked to the storage and their parameters, as opposed to storage parameters. Again, considering the

these efficiencies are referred to as 'TechnologyToStorage' and 'Technology-FromStorage'. These parameters also serve to define which technologies are linked to which storage facilities. The net charge within a time slice is obtained through multiplication of the charging minus the discharging rate with the duration of that time slice (S3 & S4).

The storage levels at the beginning and end of each year, season and day-type are calculated by summing up the net charges over all preceding time slices (S5 – S15), starting from a specified level at the beginning of the first year of the modelling period. This allows calculating the storage levels indicated as [A, F, K, P] in Fig. 5. The net charge is added to these levels during one daily time bracket after another throughout the following day to verify if the storage levels are within their minimum and maximum (SC1 & SC4) [A, B, C, F, G, H, K, L, M]. Similarly, the net charge is subtracted to assess storage levels in the previous day (SC2 & SC3) [F, E, D, K, J, I, P, O, N].

The maximum capacity (SI1) is composed of the accumulated storage additions minus retirements based on the lifetime of the storage (SI3), plus all exogenously given capacities. Exogenous capacities may be composed of residual capacities from before the modelling period, or capacity additions which are scheduled to happen within the modelling period[101]. The minimum capacity is defined as a fraction of the maximum capacity (SI2). It serves to ensure that the storage unit is never emptied completely, e.g., to increase the lifetime of batteries.

Next, the investments in storage are calculated in order to be able to integrate the storage equations into the objective function and ensure overall system costs are minimised[102]. The required investments are assumed to be directly proportional to the additional storage capacities, which are measured in terms of stored energy (SI4). Further, the salvage value of a storage facility at the end of the modelling period is calculated (SI6 – SI8). Both, the investments in storage

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pumped storage example, the capacity of the turbine (e.g., in MW) limits the rate at which electricity may be generated, while the upper minus the minimum level of the dam constrains the storage capacity (e.g., in MWh).

101 For example, the construction of a reservoir of a pumped storage hydropower plant is decided years before its actual implementation. If such an investment is defined exogenously, it will not be part of the optimisation and its costs will not be accounted for in the model.

102 This is only required if the model should have the capability to optimise storage capacity additions. Alternatively, all storage capacities and their lower and upper limits could be defined exogenously as parameters.

and the salvage values are discounted to the beginning of the first year of the modelling period (SI5 & SI9). The total discounted storage cost is obtained by subtracting the salvage values from the capital investments (SI10).

Storage is integrated into the core code similarly to the prioritisation of demand types and demand shifting through the equations (OBJ_rev, Acc4_rev, TDC1_rev & TDC2c)[103]. They ensure that storage related costs are minimised as part of the objective function.

2.2.5 Bringing It All Together

Some modifications are required in order to integrate all code additions into the core code of OSeMOSYS[104]. In the individual code blocks for prioritising demand types and demand shifting, only up to a predefined fraction is allowed to remain unmet (UD1) or to be shifted (DS4). It needs to be specified how the model reacts when both occur at the same time. For this purpose it is simply assumed that whatever is greater, the maximum share of the demand which may be shifted or the maximum share of the unmet demand, determines the minimum amount which has to be met instantly For example, if 10% are allowed to remain unmet and 30% may be shifted, then 70% have to be supplied at exactly the time when the demand occurs (D4 & D5).

The remaining modifications of the core code are similar to the previous additions: the rate of demand of the core code is adjusted to include flexible demand types (D1, EQ_rev = D2) and the new cost components are integrated to allow for their minimisation as part of the objective function (OBJ_rev, Acc4_rev, TDC1_rev & TDC2). As equation (D3) defines flexible demand for both, prioritisation of demand and demand shifting, it only needs to be added once. With these final steps, OSeMOSYS will be able to model variable electricity generation and find the optimal mix between storing energy and shifting certain demand types while considering their different priorities.

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[103] However, in this case there is no need to modify any demand related calculations of the core code.

[104] Adding all the combined blocks to the original code does not require each of them to be used in a model run. The blocks that actually have to be used are defined by the data file.

2.3 Algebraic Formulation

2.3.1 General

Section 2.3 of Part A of this thesis explains the mathematical formulations used to model the enhanced functionality outlined in Section 2.2 of Part A of this thesis[105]. Refer to Section 2.4 for an application.

All code additions presented in Section 2.3 refer to the core model code[106] in its version of 8 November 2011, as downloadable via the OSeMOSYS website (www.osemosys.org). However, the previous basic storage equations (denoted in the OSeMOSYS code as S1 – S6) have been removed since they were replaced by a more elaborate storage model[107].

Box 1 provides a brief explanation of all indices used in the algebraic formulations.

Box 1: Indices Used in Equations to Model Elements of Smart Grids

Squared brackets indicate the values these indices might have. Note that they are sequential, i.e., season 4 follows season 3, day-type 2 follows day-type 1, etc.

y	…	Year [sy = start year, sy+1, sy+2, …, fy = final year]
yy	…	Same as year; used in equations if two independent indices for years are required (e.g., equation SI3 mentioned in the online supplement, chapter 1.2: Storage)
l	…	Time slice: i.e., a fraction of the year with specific load characteristics.
ls	…	Season [1, 2, …, fls = final season]: e.g., winter and summer
ld	…	Day-type [1, 2, …, fld = final day-type]: e.g., weekdays and weekends.
lh	…	Daily time bracket [1, 2, …, flh = final time bracket]: i.e., a timespan within one specific day
lhlh	…	Same as daily time bracket; used in equations if two independent indices for

105 This section strongly relates to the nomenclature used in the core code of OSeMOSYS. Howells et al. [101] provide a more conceptual understanding for how the core code is set up.

106 For an explanation of elements of the core model code refer to Howells et al. [101].

107 The storage equations S1 – S6 of the core code required the user to exactly know at what times extremes in the storage levels will occur. Further, they did not allow for an accurate calculation of storage costs and an optimisation of the overall available storage capacity.

		daily time brackets are required, e.g., to describe a summation over daily time brackets lhlh up to a specific lh (e.g., equation DS11 mentioned in the online supplement, chapter 1.1: Demand Shifting)
r	…	Region
f	…	Fuel
fdt	…	Flexible demand type, each with a different demand profile and degrees of flexibility
t	…	Technology: e.g., a group of hydropower plants or a PV panel or an inverter
s	…	Storage technology: e.g., one specific dam or a bank of batteries
m	…	Mode of operation: A storage facility should be charged during the operation of one or more technologies in one specified mode of operation and discharged in another.

Whenever the following text refers to a rate (e.g., the rate of charging a storage facility, the rate of activity of a technology), it is measured in units of power rather than units of energy. All parameters which need to be entered by the analyst are described in Box 2 for all code blocks combined. They are indicated in bold within the equations below to differentiate them from model variables. Complying with the OSeMOSYS naming convention, rather long parameter and variable names were chosen to increase readability.

Box 2: Parameters used to Model Elements of Smart Grids

AvailabilityFactor$_{\mathbf{y,t,r}}$ – One minus the fraction of the year during which planned maintenance takes place.

CapacityFactor$_{\mathbf{y,t,r}}$ – The ratio of available maximum capacity to the design capacity.

CapacityToActivityUnit$_{\mathbf{t,r}}$ – Relates the unit that capacity is measured in to the unit of activity.

CapitalCostStorage$_{\mathbf{s,y,r}}$ – Investment costs of storage additions, defined per unit of storage capacity.

Conversion$_{\mathbf{ls,l/ld,l/lh,l}}$ – Conversion factors to relate a time slice to a season, day-type and daily time bracket.

CostFactorShiftedDemand$_{\mathbf{fdt}}$ – Cost of shifting a load by one hour.

DaysInDayType$_{y,ls,ld}$ – Number of days for each day-type within a week, i.e., out of seven.

DaySplit$_{y,lh}$ – Defines the length of one daily time bracket in one specific day as a fraction of the year[108].

DiscountRateDemand – Discount rate applied to demand related costs, e.g., due to demand which is not met or shifted.

DiscountRateStorage$_{s,r}$ – Discount rate applied to storage related investment costs.

MaxAdvance$_{fdt}$ – Maximum number of time brackets a load may be met earlier within a day.

MaxDelay$_{fdt}$ – Maximum number of time brackets a load may be delayed within a day.

MaxShareShiftedDemand$_{y,fdt,f,r}$ – Fraction of flexible demand which can be shifted during a day.

MaxShareUnmetDemand$_{y,fdt,f,r}$ – Fraction of flexible demand which can remain unmet within each daily time bracket.

MinStorageCharge$_{s,y,r}$ – Minimum storage capacity as a fraction of the maximum capacity.

OperationalLifeStorage$_{s,r}$ – Lifetime of storage options added by OSeMOSYS. This parameter does not affect exogenously defined 'residual storage capacities'.

PriceOfUnmetDemand$_{y,fdt,f,r}$ – Penalty per unit of energy for not meeting a demand.

ResidualStorageCapacity$_{s,y,r}$ – Exogenously defined storage capacities.

SpecifiedAnnualStandardDemand$_{y,f,r}$ – Requirement for each output fuel throughout a year which has to be met instantly when it occurs.

SpecifiedAnnualStandardDemandProfile$_{y,l,f,r}$ – Indicates the proportion of energy demand in each time slice. For each year, the sum must be equal to one.

SpecifiedDailyFlexibleDemand$_{y,fdt,ls,ld,f,r}$ – Requirement for each output fuel throughout one day of a specific day-type, season and year which can be met flexibly throughout the day.

SpecifiedDailyFlexibleDemandProfile$_{y,fdt,ls,ld,lh,f,r}$ – Indicates the proportion of flexible energy demand in each daily time bracket. For each day, the sum must be equal to one.

StorageLevelStart$_{s,r}$ – Available storage capacity at beginning of the modelling period.

StorageMaxChargeRate$_{s,r}$ – Maximum rate at which a storage option may be charged.

StorageMaxDischargeRate$_{s,r}$ – Maximum rate at which a storage option may be discharged.

TechnologyFromStorage$_{t,m,s,r}$ – Links technologies to a storage option in one mode of operation, and defines their discharging efficiency. A value of one equals an efficiency of 100%.

TechnologyToStorage$_{t,m,s,r}$ – Links technologies to a storage option in another mode of operation, and defines their charging efficiency. A value of one equals an efficiency of 100%.

TechWithCapacityNeededToMeetPeakTS$_{t,r}$ – Set equal to one for technologies which

[108] Analogue to the YearSplit parameter.

have to satisfy a demand instantly (e.g., power plants) and zero for technologies which only need to be designed to meet a yearly demand (e.g., oil refineries).

YearSplit$_{y,l}$ – The length of each time slice as a fraction of the year. Its sum over a year should equal one.

2.3.2 Variability in Electricity Generation

In order to better model variable electricity generation, the dimensions of the capacity factor are extended to include time slices in addition to years. In the core code of OSeMOSYS, the capacity factor appears in the equations (CAa4) and (CAb1).

(CAb1) ensures that all technologies have enough capacity available to satisfy an overall yearly demand. Their annual production, i.e., the sum of their production in each time slice, has to be less than their total available capacity multiplied by the fraction of the year for which the technology is available, and further de-rated by the capacity factor.

(CAa4) differentiates additionally between technologies which have to have enough capacity to satisfy a demand instantly throughout the year[109]. Their capacity de-rated by the capacity factor has to be larger than their rate of activity during any time slice.

In the core code of OSeMOSYS, any rate is measured in units of energy per time, e.g., petajoule/year. Capacities might be measured in a different unit, e.g., gigawatt. The CapacityToActivityUnit is therefore required to ensure that the same units apply on both sides of the equation[110]. In both equations, the

[109] E.g., while a power plant is generating electricity to meet demand instantly, an oil refinery might only need to be designed to meet the yearly demand for oil. This would require enough storage capacities to balance yearly fluctuations as a precondition.

[110] The CapacityToActivityUnit is equal to the number of units of energy which could be produced at a constant power output of one unit of capacity. However, if GWa was chosen as the unit for energy and GW for capacities, any rate would as well be measured in GW (=GWa/a). The CapacityToActivityUnit would then equal one. 1 GWa is the amount of energy a technology with a capacity of 1GW could generate throughout a year at maximum operation, i.e., 1 GWa = 365*24 GWh.

'CapacityToActivityUnit' parameter allows converting capacity units to activity units[111].

$$\forall_{y,t,r}: \sum_l RateOfTotalActivity_{y,l,t,r} * \boldsymbol{YearSplit_{y,l}} \leq TotalCapacityAnnual_{y,t,r} * \boldsymbol{CapacityFactor_{y,t,r}} * \boldsymbol{AvailabilityFactor_{y,t,r}} * \boldsymbol{CapacityToActicityUnit_{t,r}} \quad \text{(CAb1)}$$

$$\forall_{y,l,t,r}: for\ \boldsymbol{TechWithCapacityNeededToMeetPeakTS_{t,r}} \neq 0: RateOfTotalActivity_{y,l,t,r} \leq TotalCapacityAnnual_{y,t,r} * \boldsymbol{CapacityFactor_{y,t,r}} * \boldsymbol{CapacityToActicityUnit_{t,r}} \quad \text{(CAa4)}$$

The time slice dimension is added by simply adding a 'l' to the indices of the 'CapacityFactor' parameter in equation (CAa4-rev). In equation (CAb1-rev) the capacity factor during each time slice additionally needs to be multiplied with the length of each time slice and summed up over the year to calculate the yearly average.

$$\forall_{y,t,r}: \sum_l RateOfTotalActivity_{y,l,t,r} * \boldsymbol{YearSplit_{y,l}} \leq \sum_l TotalCapacityAnnual_{y,t,r} * \boldsymbol{CapacityFactor_{y,t,l,r}} * \boldsymbol{YearSplit_{y,l}} * \boldsymbol{AvailabilityFactor_{y,t,r}} * \boldsymbol{CapacityToActicityUnit_{t,r}} \quad \text{(CAb1-rev)}$$

$$\forall_{y,l,t,r}: for\ \boldsymbol{TechWithCapacityNeededToMeetPeakTS_{t,r}} \neq 0: RateOfTotalActivity_{y,l,t,r} \leq TotalCapacityAnnual_{y,t,r} * \boldsymbol{CapacityFactor_{y,t,l,r}} * \boldsymbol{CapacityToActicityUnit_{t,r}} \quad \text{(CAa4-rev)}$$

With these changes, variable electricity generation can be modelled as an integral part of OSeMOSYS.

2.3.3 Prioritising Demand Types

2.3.3.1 Derived Variables and Constraints

First, the rate of a flexible demand is calculated for each season, day-type and daily time bracket in a year. The overall daily demand is multiplied with the proportion of this demand within each daily time bracket, divided by its length (D3).

[111] E.g., to relate MW of capacity to GWh of production.

$$\forall_{fdt,y,ls,ld,lh,f,r}\colon RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} = \boldsymbol{SpecifiedDailyFlexibleDemand_{fdt,y,ls,ld,f,r}} * \boldsymbol{SpecifiedDailyFlexibleDemandProfile_{fdt,y,ls,ld,lh,f,r}} / \boldsymbol{DaySplit_{y,lh}} \quad \text{(D3)}$$

Within each daily time bracket, only up to a predefined fraction of the demand is allowed to remain unmet (UD1).

$$\forall_{fdt,y,ls,ld,lh,f,r}\colon RateOfUnmetDemand_{fdt,y,ls,ld,lh,f,r} \le \boldsymbol{MaxShareUnmetDemand_{fdt,y,f,r}} * RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} \quad \text{(UD1)}$$

In order to calculate the unmet demand, its rate is converted back from seasons, day-types and daily time brackets to time slices (UD2).

$$\forall_{fdt,y,l,f,r}\colon UnmetDemand_{fdt,y,l,f,r} = \sum_{ls,ld,lh}(RateOfUnmetDemand_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{Conversion_{l,ls}} * \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}}) * \boldsymbol{YearSplit_{y,l}} \quad \text{(UD2)}$$

The unmet demand is summed up over all time slices to get the annual unmet demand (UD3).

$$\forall_{fdt,y,f,r}\colon UnmetDemandAnnual_{fdt,y,f,r} = \sum_{l} RateOfUnmetDemand_{fdt,y,l,f,r} \quad \text{(UD3)}$$

Its cost is calculated (UD4) and discounted back to the first year, assuming they would be incurred at approximately the middle of each year (UD5).

$$\forall_{fdt,y,r}\colon CostOfUnmetDemand_{fdt,y,r} = \sum_{f} UnmetDemandAnnual_{fdt,y,f,r} * \boldsymbol{PriceOfUnmetDemand_{fdt,y,f,r}} \quad \text{(UD4)}$$

$$\forall_{fdt,y,r}\colon DiscountedCostOfUnmetDemand_{fdt,y,r} = \frac{CostOfUnmetDemand_{fdt,y,r}}{(1+\boldsymbol{DiscountRateDemand})^{y-\min(y)+0.5}} \quad \text{(UD5)}$$

2.3.3.2 Integrating the Prioritisation of Demand Types

Integrating Unmet Demand into the Overall Demand

The rate of demand of the core code of OSeMOSYS needs to be modified, as demand is now composed of a standard demand as used in the core model, plus flexible demand types. Flexible demand may be reduced by not meeting parts of it in a given time slice. Conversion factors are used to convert a flexible demand back from seasons, day-types and daily time brackets to time slices, as used in the core model (D1a).

$$\forall_{y,l,f,r}: RateOfDemand_{y,l,f,r} = RateOfStandardDemand_{y,l,f,r} + \sum_{fdt,ls,ld,lh}\big(RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} - -RateOfUnmetDemand_{fdt,y,ls,ld,lh,f,r}\big) * \boldsymbol{Conversion_{l,ls}} * \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}} \quad \text{(D1a)}$$

The terms in the demand equation of the core code (EQ) have to be renamed to differentiate the overall demand, which includes flexible demand, from the demand as defined in the core code. This demand as defined previously is now called standard demand (EQ_rev = D2).

$$\forall_{y,l,f,r}:\ RateOfDemand_{y,l,f,r} = \boldsymbol{SpecifiedAnnualDemand_{y,f,r}} * \boldsymbol{SpecifiedDemandProfile_{y,l,f,r}} * \boldsymbol{YearSplit_{y,l}} \quad \text{(EQ)}$$

$$\forall_{y,l,f,r}: RateOfStandardDemand_{y,l,f,r} = \boldsymbol{SpecifiedAnnualStandardDemand_{y,f,r}} * \boldsymbol{SpecifiedAnnualStandardDemandProfile_{y,l,f,r}/YearSplit_{y,l}} \quad \text{(EQ\_rev = D2)}$$

Integrating the Costs of not Meeting Demand

The original objective function of the core model (OBJ) is limited to costs of technologies. It therefore needs to be modified by removing its reference to technologies (OBJ_rev). This increases its applicability and allows including the cost of not meeting a demand as part of the total discounted costs.

$$minimise \sum_{y,t,r} TotalDiscountedCost_{y,t,r} \quad \text{(OBJ)}$$

$$minimise \sum_{y,r} TotalDiscountedCost_{y,r} \quad \text{(OBJ\_rev)}$$

This change directly affects equation (Acc4), which does not need to be summed up over each technology any longer (Acc4_rev).

$$\forall_r: ModelPeriodCostByRegion_r = \sum_{y,t} TotalDiscountedCost_{y,t,r} \quad \text{(Acc4)}$$

$$\forall_r: ModelPeriodCostByRegion_r = \sum_{y} TotalDiscountedCost_{y,r} \quad \text{(Acc4\_rev)}$$

As total discounted costs of the core model just relate to costs of technologies (TDC1), they are renamed accordingly (TDC1_rev).

$$\forall_{y,t,r}:\ TotalDiscountedCost_{y,t,r} = DiscountedOperatingCost_{y,t,r} + DiscountedCaptialInvestment_{y,t,r} + DiscountedTechnologyEmissionsPenalty_{y,t,r} - DiscountedSalvageValue_{y,t,r} \quad \text{(TDC1)}$$

$$\forall_{s,y,r}\text{: } TotalDiscountedCostByTechnology_{y,t,r} = DiscountedOperatingCost_{y,t,r} + DiscountedCaptialInvestment_{y,t,r} + DiscountedTechnologyEmissionsPenalty_{y,t,r} - DiscountedSalvageValue_{y,t,r} \quad \text{(TDC1\_rev)}$$

This allows for a modified calculation of the total discounted costs, where the overall costs of not meeting a demand are included and added to the overall technology related costs (TDC2a).

$$\forall_{s,r}\text{: } TotalDiscountedCost_{y,r} = \sum_t TotalDiscountedCostByTechnology_{y,t,r} + \sum_{fdt} DiscountedCostOfUnmetDemand_{fdt,y,r} \quad \text{(TDC2a)}$$

With this final step, the cost for not meeting any demand will be minimised as part of the objective function.

2.3.4 Demand Shifting

2.3.4.1 Derived Variables

Several demand types that can be shifted may be entered. These demand types are characterised by entering an overall daily demand with a specific demand profile. The rate of such a flexible demand is then calculated for each season, day-type and daily time bracket (D3). As all relevant equations are valid individually for each flexible load type, it can be assumed that each flexible demand is stored in a different 'storage'.

$$\forall_{fdt,y,ls,ld,lh,f,r}\text{: } RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} = \boldsymbol{SpecifiedDailyFlexibleDemand_{fdt,y,ls,ld,f,r}} * \boldsymbol{SpecifiedDailyFlexibleDemandProfile_{fdt,y,ls,ld,lh,f,r}} / \boldsymbol{DaySplit_{y,lh}} \quad \text{(D3)}$$

The net charge of these storages is split up between the net charge of loads which are met in advance and those which are postponed. As with the flexible demand types, the storage to meet delayed loads can be seen as independent from the storage to meet demand in advance (DS1)[112].

[112] However, only up to a predefined fraction of a flexible demand may be shifted at any given time. This fraction is shared between demand which is postponed and demand which has to be met earlier.

$$\forall_{fdt,y,ls,ld,lh,f,r}: RateOfNetCharge_{fdt,y,ls,ld,lh,f,r} = RateOfNetChargeDelayed_{fdt,y,ls,ld,lh,f,r} + RateOfNetChargeAdvanced_{fdt,y,ls,ld,lh,f,r} \quad \text{(DS1)}$$

The net charge is then calculated for both, delayed loads (DS2) and those which are met in advance (DS3), as the charge minus the discharge.

$$\forall_{fdt,y,ls,ld,lh,f,r}: RateOfNetChargeDelayed_{fdt,y,ls,ld,lh,f,r} = RateOfChargeDelayed_{fdt,y,ls,ld,lh,f,r} - RateOfDischargeDelayed_{fdt,y,ls,ld,lh,f,r} \quad \text{(DS2)}$$

$$\forall_{fdt,y,ls,ld,lh,f,r}: RateOfNetChargeAdvanced_{fdt,y,ls,ld,lh,f,r} = RateOfChargeAdvanced_{fdt,y,ls,ld,lh,f,r} - RateOfDischargeAdvanced_{fdt,y,ls,ld,lh,f,r} \quad \text{(DS3)}$$

2.3.4.2 Constraints

Within each daily time bracket, only up to a predefined fraction of the demand can be either postponed or met earlier (DS4).

$$\forall_{fdt,y,ls,ld,lh,f,r}: RateOfChargeDelayed_{fdt,y,ls,ld,lh,f,r} + RateOfChargeAdvanced_{fdt,y,ls,ld,lh,f,r} \leq \boldsymbol{MaxShareShiftedDemand_{y,fdt,f,r}} * RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} \quad \text{(DS4)}$$

Next, constraints are described separately for loads which are met later and those which are shifted to earlier times. However, these constraints do not set a limit on the maximum share an exogenously defined demand may be increased through demand shifting. This means that theoretically a large demand which was supposed to be met at a specific time could be moved to another time where hardly any original demand occurred. In cases where this is not considered realistic, a simple new constraint similar to (DS4) would need to be formulated, just for the rate of discharging instead of the rate of charging.

Calculation of Delayed Loads

For each day, the overall charge has to equal the overall discharge, i.e., the storage is empty again after each day[113].

$$\forall_{fdt,y,ls,ld,f,r}: \sum_{lh} RateOfChargeDelayed_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \leq \sum_{lh} RateOfDischargeDelayed_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \quad \text{(DS5)}$$

Up to every time bracket within a day, at maximum the amount can be discharged which was charged beforehand, i.e., the storage can't be discharged below zero (DS6).

$$\forall_{fdt,y,ls,ld,lh,f,r}: for\ x = 1\ to\ flh\colon \sum_{lh=1}^{x} RateOfChargeDelayed_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \geq \sum_{lh=1}^{x} RateOfDischargeDelayed_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \quad \text{(DS6)}$$

To ensure that each load is met within a specified delay, the charge up to every time bracket within a day has to be lower than[114], or equal to, what will be discharged up to this time bracket plus the maximum delay (DS7)[115].

$$\forall_{fdt,y,ls,ld,lh,f,r}: for\ x = 1\ to\ \left(fh - \boldsymbol{MaxDelay_{fdt}}\right)\colon \sum_{lh=1}^{x} RateOfChargeDelayed_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \leq \sum_{lh=1}^{x+\boldsymbol{MaxDelay_{fdt}}} RateOfDischargeDelayed_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \quad \text{(DS7)}$$

113 Not using the equal sign may support the mathematical solver in finding a solution. The actual rate of the delayed discharge will not be higher as the rate of charge, as this would involve a higher demand and ultimately higher costs. The rates are multiplied with the duration of each daily time bracket to allow for time brackets with individually varying durations.

114 Note that charging is not necessarily required to be equal to the discharging, as a charging occurring after the assessed time bracket could as well still be discharged within the maximum delay.

115 Due to the integration of the charge up to the final time bracket minus the maximum delay, this equation does not control what is happening in the last time period within a day-type. However, (DS5) ensures that this does not lead to charges being delayed without being met within this last period.

Calculation of Loads Met Earlier ('Advanced Loads')

The following equations follow the same logic as the equations for the delayed loads. For every day the overall charge has to equal the overall discharge, except that in this case the assumed storage is required to be *full* again after each day (DS8). This means that the storage first has to be discharged before it can be charged, i.e., the storage can be used from the very beginning of a day-type to meet loads in advance which would actually occur later.

$$\forall_{fdt,y,ls,ld,f,r}: \sum_{lh} RateOfChargeAdvanced_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \leq \sum_{lh} RateOfDischargeAdvanced_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \quad \text{(DS8)}$$

Up to every time bracket within a day, only at maximum the amount can be charged which was discharged beforehand (DS9). This means that the storage cannot be charged above its capacity, given that it is assumed to be full in the very morning.

$$\forall_{fdt,y,ls,ld,lh,f,r}: for\ x = 1\ to\ flh: \sum_{lh=1}^{x} RateOfChargeAdvanced_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \leq \sum_{lh=1}^{x} RateOfDischargeAdvanced_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \quad \text{(DS9)}$$

To ensure that each load is met within a specified time in advance, the discharge up to every time bracket minus the maximum time that loads can be advanced has to be lower than[116], or equal to, the charge up to this time bracket (DS10).

$$\forall_{fdt,y,ls,ld,lh,f,r}: for\ x = 1\ to\ (flh - \boldsymbol{MaxAdvance_{fdt}}): \sum_{lh=1}^{x+\boldsymbol{MaxAdvance_{fdt}}} RateOfChargeAdvanced_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \geq \sum_{lh=1}^{x} RateOfDischargeAdvanced_{fdt,y,ls,ld,lh,f,r} * \boldsymbol{DaySplit_{y,lh}} \quad \text{(DS10)}$$

116 Note that it is not necessarily required to be equal to the charge, as a discharge occurring after the assessed time bracket could as well still be charged within the maximum time that loads can be delayed.

2.3.4.3 Minimising the Use of Flexibility

The following equations sum up the all demand met later (DS11) and earlier (DS12), multiplied with the duration of every daily time bracket in which they are not met. For example, a capacity of 100 kW is assumed to be required for two hours. If this demand is shifted by 4 hours, (DS11) and (DS12) would return a value of 800 (100 kW x 2 hours x 4 hours). As the duration of a daily time bracket is entered as a fraction of the year, it needs to be multiplied with the hours within a year to receive values related to hours. Note that these equations refer to the loads shifted within one specific day.

$$\forall_{fdt,y,ls,ld,f,r}: SumOfDailyNetChargeDelayed_{fdt,y,ls,ld,f,r} = \sum_{lhlh=1}^{flh} \boldsymbol{DaySplit_{y,lhlh}} * 365 * 24 * \sum_{lh=1}^{lhlh} (RateOfChargeDelayed_{fdt,y,ls,ld,lh,f,r} - RateOfDischargeDelayed_{fdt,y,ls,ld,lh,f,r}) * \boldsymbol{DaySplit_{y,lh}} * 365 * 24 \quad \text{(DS11)}$$

$$\forall_{fdt,y,ls,ld,f,r}: SumOfDailyNetChargeAdvanced_{fdt,y,ls,ld,f,r} = \sum_{lhlh=1}^{flh} \boldsymbol{DaySplit_{y,lhlh}} * 365 * 24 * \sum_{lh=1}^{lhlh} (RateOfDischargeAdvanced_{fdt,y,ls,ld,lh,f,r} - RateOfChargeAdvanced_{fdt,y,ls,ld,lh,f,r}) * \boldsymbol{DaySplit_{y,lh}} * 365 * 24 \quad \text{(DS12)}$$

The weeks within a season can be calculated by summing up the length of all time slices which relate to this season, multiplied by the number of weeks per year. Conversion factors have to be used to assign the length of time slices to a season, daily time bracket and day-type.

$$\sum_{l,ld,lh} \boldsymbol{YearSplit_{y,l}} * \boldsymbol{Conversion_{ls,l}} * \boldsymbol{Conversion_{ld,l}} * \boldsymbol{Conversion_{lh,l}} * 52 \quad \text{(-)}$$

The costs for shifting loads are then calculated by adding the equations (DS11) and (DS12), multiplying them with the number of weekdays within a day-type and summing them up for each day-type and fuel. This is then multiplied by all weeks within a season as described above and summed up over all seasons. The result is then multiplied by a cost factor which represents the cost of shifting demand by one hour.

$$\forall_{fdt,y,r}: CostOfShiftedDemand_{fdt,y,r} = \boldsymbol{CostFactorShiftedDemand_{ftd}} * \sum_{ls} \{ \sum_{ld,f} (SumOfDailyNetChargeDelayed_{fdt,y,ls,ld,f,r} + SumOfDailyNetChargeAdvanced_{fdt,y,ls,ld,f,r}) * \boldsymbol{DaysInDayType_{y,ls,ld}} * \sum_{l,ld,lh} \boldsymbol{YearSplit_{y,l}} * \boldsymbol{Conversion_{ls,l}} * \boldsymbol{Conversion_{ld,l}} * \boldsymbol{Conversion_{lh,l}} * 52 \} \quad \text{(DS13)}$$

The costs are then discounted back to the first year, assuming they would be incurred at approximately the middle of each year (UD5).

$$\forall_{fdt,y,r}: DiscountedCostOfShiftedDemand_{fdt,y,r} = \frac{CostOfShiftedDemand_{fdt,y,r}}{(1+\boldsymbol{DiscountRateDemand})^{y-\min(y)+0.5}} \quad \text{(DS14)}$$

2.3.4.4 Integrating Demand Shifting

Integrating Demand Shifting into the Overall Demand

Similarly as with the prioritisation of demand, the overall demand is defined as a standard demand as used in the core model, plus flexible demand types. The net charge of the assumed storage is subtracted from the flexible demand. Conversion factors are used to convert a flexible demand back from seasons, day-types and daily time brackets to time slices (D1b).

$$\forall_{y,l,f,r}: RateOfDemand_{y,l,f,r} = RateOfStandardDemand_{y,l,f,r} + \sum_{fdt,ls,ld,lh}\left(RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} - RateOfNetCharge_{fdt,y,ls,ld,lh,f,r}\right) * \boldsymbol{Conversion_{l,ls}} * \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}} \quad \text{(D1b)}$$

The demand as defined in the core code of OSeMOSYS (EQ) is renamed to standard demand to differentiate it from flexible demand (EQ_rev = D2).

$$\forall_{y,l,f,r}: RateOfStandardDemand_{y,l,f,r} = \boldsymbol{SpecifiedAnnualStandardDemand_{y,f,r}} * \boldsymbol{SpecifiedAnnualStandardDemandProfile_{y,l,f,r}} / \boldsymbol{YearSplit_{y,l}} \quad \text{(EQ\_rev = D2)}$$

Integrating the Costs of Demand Shifting

As with the prioritisation of demand, the original objective function of the core model (OBJ) needs to be modified to allow for the inclusion of other than technology related costs (OBJ_rev). Equation (Acc4) does not need to be summed up over each technology any longer (Acc4_rev) and the total discounted costs (TDC1) are renamed to indicate that they just relate to costs of technologies (TDC1_rev).

$$minimise \sum_{y,r} TotalDiscountedCost_{y,r} \quad \text{(OBJ\_rev)}$$

$$\forall_{r}: ModelPeriodCostByRegion_{r} = \sum_{y} TotalDiscountedCost_{y,r} \quad \text{(Acc4\_rev)}$$

$$\forall_{s,y,r}: TotalDiscountedCostByTechnology_{y,t,r} = DiscountedOperatingCost_{y,t,r} + DiscountedCaptialInvestment_{y,t,r} + DiscountedTechnologyEmissionsPenalty_{y,t,r} - DiscountedSalvageValue_{y,t,r} \quad \text{(TDC1\_rev)}$$

This allows for a modified calculation of the total discounted costs, which adds the overall costs of shifting demand to the overall technology related costs (TDC2a).

$$\forall_{s,r}: TotalDiscountedCost_{y,r} = \sum_{t} TotalDiscountedCostByTechnology_{y,t,r} + \sum_{fdt} DiscountedCostOfShiftedDemand_{fdt,y,r} \quad \text{(TDC2b)}$$

With this final step, the cost for not meeting any demand will be minimised as part of the objective function.

2.3.5 Storage

2.3.5.1 General Storage Equations

Within this section, a letter within squared brackets, e.g., [A], indicates that the following equation is required to calculate the storage level for this point as shown in Fig. 5. The figure supports the explanations of the following storage equations. It illustrates the very first and last week of Season 3. Overall, 4 seasons, 2 day-types (weekdays from Monday until Friday and weekends) and 3 daily time brackets are assumed for these explanations.

Charging and Discharging

The rate of activity of a technology is multiplied with the efficiency of storing energy to a storage facility to calculate the rate of charge. OSeMOSYS calculates the rate of activity of a technology for each time slice. To relate it to seasons, day-types and daily time brackets, conversion factors are required (S1).

$$\forall_{s,y,ls,ld,lh,r}: RateOfStorageCharge_{s,y,ls,ld,lh,r} = for\ \boldsymbol{TechnologyToStorage_{t,m,s,r}} > 0: \sum_{t,m,l} RateOfActivity_{y,l,t,m,r} * \boldsymbol{TechnologyToStorage_{t,m,s,r}} * \boldsymbol{Conversion_{l,ls}} * \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}} \quad \text{(S1)}$$

Similarly, the rate of activity of a technology is multiplied with the efficiency of retrieving energy from the storage facility to calculate the rate of discharge (S2).

$$\forall_{s,y,ls,ld,lh,r}: \\ RateOfStorageCharge_{s,y,ls,ld,lh,r} = for\ \boldsymbol{TechnologyFromStorage_{t,m,s,r}} > 0: \\ \sum_{t,m,l} RateOfActivity_{y,l,t,m,r} * \boldsymbol{TechnologyFromStorage_{t,m,s,r}} * \boldsymbol{Conversion_{l,ls}} * \\ \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}} \quad \text{(S2)}$$

The net charge over the entire year in a given daily time bracket, day-type and season is calculated as the difference between the rate of charging minus the rate of discharging, multiplied by the length of the corresponding time slice (S3).

$$\forall_{s,y,ls,ld,lh,r}: NetChargeWithinYear_{s,y,ls,ld,lh,r} = (RateOfStorageCharge_{s,y,ls,ld,lh,r} - \\ RateOfStorageDischarge_{s,y,ls,ld,lh,r}) * \boldsymbol{YearSplit_{y,l}} * \boldsymbol{Conversion_{l,ls}} * \\ \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}} \quad \text{(S3)}$$

Similarly, the net charge in a given time bracket within one specific day of a given day-type and season is calculated as the difference between the rate of charging minus the rate of discharging, multiplied by the length of the daily time bracket (S4).

$$\forall_{s,y,ls,ld,lh,r}: NetChargeWithinDay_{s,y,ls,ld,lh,r} = (RateOfStorageCharge_{s,y,ls,ld,lh,r} - \\ RateOfStorageDischarge_{s,y,ls,ld,lh,r}) * DaySplit_{y,lh} \quad \text{(S4)}$$

Storage Levels at the Beginning and End of each Year

For the start of the very first year, the storage level is given by the analyst (S5).

$$\forall_{s,y,r}: for\ y = sy: StorageLevelYearStart_{s,y,r} = StorageLevelStart_{s,r} \quad \text{(S5)}$$

For subsequent years, the start level of the previous year is augmented by the net charge over all daily time brackets, day-types and seasons of that previous year (S6).

$$\forall_{s,y,r}: for\ y > sy: StorageLevelYearStart_{s,y,r} = StorageLevelYearStart_{s,y-1,r} + \\ \sum_{ls,ld,lh} NetChargeWithinYear_{s,y-1,ls,ld,lh,r} \quad \text{(S6)}$$

The final conditions at the end of each year are equal to the start levels of the following year (S7). The only exception is the very last year, as in this case there is no year to follow.

$$\forall_{s,y,r}: for\ y < fy:$$
$$\mathrm{StorageLevelYearFinish}_{\mathrm{s,y,r}} = \mathrm{StorageLevelYearStart}_{\mathrm{s,y+1,r}} \tag{S7}$$

For the last year, the final conditions at the very end of that year are calculated as the start level of the final year plus the net charge over all daily time brackets, day-types and seasons of the final year (S8)[117].

$$\forall_{s,y,r}: for\ y = fy: StorageLevelYearFinish_{s,y,r} = StorageLevelYearStart_{s,y,r} + \sum_{ls,ld,lh} NetChargeWithinYear_{s,y,ls,ld,lh,r} \tag{S8}$$

Storage Levels at the Beginning of each Season

The start conditions at the beginning of the very first season in each year are equal to the start levels in each year (S9).

$$\forall_{s,y,ls,r}:$$
$$for\ ls = 1: StorageLevelSeasonStart_{s,y,ls,r} = StorageLevelYearStart_{s,y,r} \tag{S9}$$

For subsequent seasons, the start conditions of the previous season are augmented by the net charge over all daily time brackets and day-types of that previous season [A] (S10).

$$\forall_{s,y,ls,r}: for\ ls > 1: StorageLevelSeasonStart_{s,y,ls,r} = StorageLevelSeasonStart_{s,y,ls-1,r} + \sum_{ld,lh} NetChargeWithinYear_{s,y,ls-1,ld,lh,r} \tag{S10}$$

[117] This equation could theoretically be avoided, if the final levels of each year were simply calculated by adding the integration of the net charge over a year to the start conditions, similarly as for (S6). (S6) could then be replaced by setting the start conditions of a year to be equal to the final conditions of the previous year. However, this would require iterating between these two equations over the years, as the start conditions are required to calculate the finish conditions and vice-versa. This would be more challenging for a solver and, e.g., in one instance GLPK had problems finding a feasible solution.

Storage Levels at the Beginning and End of each Day-type

The start conditions at the beginning of the very first day-type in each season are equal to the start levels in each season [A] (S11).

$$\forall_{s,y,ls,ld,r}: for\ ld = 1:$$
$$StorageLevelDayTypeStart_{s,y,ls,ld,r} = StorageLevelSeasonStart_{s,y,ls,r} \quad \text{(S11)}$$

For subsequent day-types, the start conditions of the previous day-type are augmented by the net charge over all daily time brackets of one day of that previous day-type, multiplied by the number of week days in this day-type [F] (S12).

$$\forall_{s,y,ls,ld,r}: for\ ld > 1:$$
$$StorageLevelDayTypeStart_{s,y,ls,ld,r} = StorageLevelDayTypeStart_{s,y,ls,ld-1,r} + \sum_{lh} NetChargeWithinDay_{s,y,ls,ld-1,lh,r} * \boldsymbol{DaysInDayType_{y,ls,ld-1}} \quad \text{(S12)}$$

The final conditions at the last day of the last season of a year have to be equal to the final conditions at the end of that year (S13).

$$\forall_{s,y,ls,ld,r}: for\ ls = fls\ \&\ ld = fld: StorageLevelDayTypeFinish_{s,y,ls,ld,r} = StorageLevelYearFinish_{s,y,r} \quad \text{(S13)}$$

For all previous seasons, the final conditions of the last day in a season are equal to the start conditions of the following season [P] (S14).

$$\forall_{s,y,ls,ld,r}: for\ ls < fls\ \&\ ld = fld: StorageLevelDayTypeFinish_{s,y,ls,ld,r} = StorageLevelSeasonStart_{s,y,ls+1,r} \quad \text{(S14)}$$

The final conditions at the end of the previous day-type in a season are equal to the final conditions of the following day-type minus the net charge over all daily time brackets within one day of that following day-type, multiplied by the number of week days in that day-type [K] (S15).

$$\forall_{s,y,ls,ld,r}: for\ (ls < fls\ \&\ ld < fld): StorageLevelDayTypeFinish_{s,y,ls,ld,r} = StorageLevelDayTypeFinish_{s,y,ls,ld+1,r} - \sum_{lh} NetChargeWithinDay_{s,y,ls,ld+1,lh,r} * DaysInDayType_{y,ls,ld+1} \quad \text{(S15)}$$

2.3.5.2 Storage Constraints

As mentioned in the previous section, it is sufficient to calculate only specific storage levels during the first and last week of a season in order to find extreme values.

Assessing the First Week of a Season

The storage level has to be within the minimum and maximum storage levels at the beginning of all daily time brackets of the first day of each day-type in the first week of a given season. This may approximate, for example, the operation during the first Monday of each season. It is calculated by adding the net charge during one time bracket after another, starting from the storage level at the beginning of the first day of the day-type [A, B, C, F, G, H] (SC1). However, this does not need to be calculated for the end of the last time bracket at the first day of a season (e.g., the first Monday in autumn, 24:00). The end of the last time bracket just has to be tested during the last day of this day-type in the first week (e.g., the first Friday in autumn, 24:00). This is because the daily storage pattern is repeated over and over again until the end of a day-type. If, e.g., a first Monday at 24:00 had an extreme storage value, it would even be more extreme at the first Friday.

$$\forall_{s,y,ls,ld,lh,r}: StorageLowerLimit_{s,y,r} \leq StorageLevelDayTypeStart_{s,y,ls,ld,r} + \sum_{lhlh\ for\ (lhlh<lh)} NetChargeWithinDay_{s,y,ls,ld,lhlh,r} \leq StorageUpperLimit_{s,y,r} \quad \text{(SC1)}$$

The storage level has to be within the minimum and maximum storage levels at the end of each daily time bracket at the last day of a given day-type in the first week of a given season. This may approximate for example the operation during the first Friday in autumn for all of its time brackets. This is calculated by subtracting the net charge backwards during one time bracket after another, starting from the start value of following day-type [F, E, D] (SC2)[118,119].

[118] Note that [F] was already tested in (SC1). This redundancy was taken into account for simplicity of the algebraic formulation.

[119] This does not need to be calculated for the last day of the last day-type in the first week (e.g., the first Sunday in autumn), as in this case it only has to be tested during the last week (e.g., the last Sunday in autumn). This is because the weekly storage pattern is repeated until the end of a season. If, for example, a first Sunday in autumn had an extreme storage value, it would even be more extreme at the end of the season. Also, it does not need to be calculated for the

$$\forall_{s,y,ls,ld,lh,r}: for\ (ld > 1): StorageLowerLimit_{s,y,r} \leq StorageLevelDayTypeStart_{s,y,ls,ld,r} - \sum_{lhlh\ for\ (lhlh>lh)} NetChargeWithinDay_{s,y,ls,ld-1,lhlh,r} \leq StorageUpperLimit_{s,y,r} \quad \text{(SC2)}$$

Assessing the Last Week of a Season

Similarly, the storage levels of the last week in a given season have to be tested to be within the minimum and maximum storage levels. At first, the levels at the end of all daily time brackets of the last day of each day-type in the last week of each season are calculated. This may approximate for example the operation during the last Friday in autumn. This is calculated by subtracting the net charge backwards during one time bracket after another, starting from the final conditions at the end of the last day of a day-type [K, J, I, P, O, N] (SC3)[120].

$$\forall_{s,y,ls,ld,lh,r}: StorageLowerLimit_{s,y,r} \leq StorageLevelDayTypeFinish_{s,y,ls,ld,r} - \sum_{lhlh\ for\ (lhlh>lh)} NetChargeWithinDay_{s,y,ls,ld,lhlh,r} \leq StorageUpperLimit_{s,y,r} \quad \text{(SC3)}$$

The storage level has to be within its bounds at the beginning of each daily time bracket for the first day of a given day-type in the last week of a given season (e.g., the last Saturday). This is calculated by adding the net charge during one time bracket after another, starting from the final conditions at the end of the previous day-type [K, L, M] (SC4)[121].

$$\forall_{s,y,ls,ld,lh,r}: for\ (ld > 1): StorageLowerLimit_{s,y,r} \leq StorageLevelDayTypeFinish_{s,y,ls,ld-1,r} + \sum_{lhlh\ for\ (lhlh>lh)} NetChargeWithinDay_{s,y,ls,ld,lhlh,r} \leq StorageUpperLimit_{s,y,r} \quad \text{(SC4)}$$

beginning of the first daily time bracket of the last day (e.g., Friday at 0:00), as this particular time of a day-type could only have an extreme value on the very first day within a season (e.g., the first Monday at 00:00).

120 Again, this does not need to be calculated for the beginning of the first time bracket (e.g., the last Friday in autumn at 00:00).

121 Similarly, this does not need to be calculated for the first day of the first day-type in the last week (e.g., the last Monday in autumn), as in this case it only has to be tested during the first week (e.g., the first Monday in autumn). Also, it does not need to be calculated for the end of the last daily time bracket of the first day (e.g., Saturday at 24:00).

Rate of Charge and Discharge

The actual charge of the storage within a daily time bracket can be limited to a predefined maximum value (SC5).

$$\forall_{s,y,ls,ld,lh,r}: \; RateOfStorageCharge_{s,y,ls,ld,lh,r} \leq \boldsymbol{StorageMaxChargeRate_{s,r}} \tag{SC5}$$

The same is true for the discharge within a daily time bracket (SC6).

$$\forall_{s,y,ls,ld,lh,r}: \; RateOfStorageDischarge_{s,y,ls,ld,lh,r} \leq \boldsymbol{StorageMaxDischargeRate_{s,r}} \tag{SC6}$$

Minimum and Maximum Storage Levels and Investments in New Storage Capacities

The upper storage limit is calculated by adding exogenously defined capacities and accumulated storage additions, minus retirements based on the lifetime of the storage (SI1).

$$\forall_{s,y,r}: \; StorageUpperLimit_{s,y,r} = AccumulatedNewStorageCapacity_{s,y,r} + \boldsymbol{ResidualStorageCapacity_{s,y,r}} \tag{SI1}$$

A lower limit is calculated as a fraction of the upper limit (SI2).

$$\forall_{s,y,r}: \; StorageLowerLimit_{s,y,r} = \boldsymbol{MinStorageCharge_{s,y,r}} * StorageUpperLimit_{s,y,r} \tag{SI2}$$

The accumulated storage additions are calculated by summing up all newly installed storage capacities until the year their operational life expires (SI3)[122].

$$\forall_{s,y,r}: \; AccumulatedNewStorageCapacity_{s,y,r} = for(yy \leq y \;\&\; \boldsymbol{OperationalLifeStorage_{s,r}} > y - yy): \; \textstyle\sum_{yy} NewStorageCapacity_{s,yy,r} \tag{SI3}$$

[122] Consider a current year y with a storage addition some years earlier in year yy. The equation tests for all capacity additions previous to y if the operational life is larger than the current year y minus yy. Only if this is the case the storage is still considered in year y. Otherwise it is assumed to be retired.

These new storage capacities require capital investments, which are directly proportional to the new capacities (SI4). The investments are then discounted to the start year (SI5).

$$\forall_{s,y,r}\colon CapitalInvestmentStorage_{s,y,r} = \\ \boldsymbol{CaptialCostStorage_{s,y,r}} * NewStorageCapacity_{s,y,r} \tag{SI4}$$

$$\forall_{s,y,r}\colon DiscountedCapitalInvestmentStorage_{s,y,r} = \\ CaptialInvestmentStorage_{s,y,r}/(1 + \boldsymbol{DiscountRateStorage_{s,r}})^{y-sy} \tag{SI5}$$

However, at the end of the modelling period capacity investments may still have a salvage value in case the storage facilities are still in operation. In all other cases, the salvage value is zero (SI6)[123].

$$\forall_{s,y,r}\colon for\ (y + \boldsymbol{OperationalLifeStorage_{s,r}} - 1 \leq fy)\colon \\ SalvageValueStorage_{s,y,r} = 0 \tag{SI6}$$

If they are still operational and if the discount rate is zero, the salvage value is simply calculated by using a linear straight-line depreciation. This means the loss in value is spread equally over the lifetime (SI7).

$$\forall_{s,y,r}\colon for\ (y + \boldsymbol{OperationalLifeStorage_{s,r}} - 1 > fy\ \& \\ \boldsymbol{DiscountRateStorage_{s,r}} = 0)\colon \\ SalvageValueStorage_{s,y,r} = CapitalInvestmentStorage_{s,y,r} * \\ (1 - (fy - y + 1)/\boldsymbol{OperationalLifeStorage_{s,r}} \tag{SI7}$$

If the discount rate is larger than zero, the salvage value is calculated by using sinking-fund depreciation, as recommended by the IAEA [86]. This method can be interpreted as setting up a fund with constant end-of-year deposits throughout the lifetime of the storage facility. The deposits are assumed to earn interest and ultimately pay for the overall investment. The salvage value is then equal to the capital investment minus the accumulated value of the fund (SI8). It needs to be highlighted that this method leads to a lower depreciation in the first and a higher one in final years, inducing the model to increasingly invest towards the end of the modelling period. If this is not deemed appropriate by the modeller, this calculation can easily be replaced by any other depreciation method.

[123] Note that an investment or capacity addition is always assumed to take place at the beginning of a year, while the salvage value is calculated for the end of the final year. If the final year fy would be 2020 and the lifetime one year, a storage addition in y = 2020 would have no salvage value, as $2020 + 1 - 1 \leq 2020$.

$$\forall_{s,y,r}\text{: } for\ (y + \boldsymbol{OperationalLifeStorage_{s,r}} - 1 > fy\ \&\ \boldsymbol{DiscountRateStorage_{s,r}} > 0)\text{:}$$
$$SalvageValueStorage_{s,y,r} = CapitalInvestmentStorage_{s,y,r} * * \left(1 - \frac{(1+\boldsymbol{DiscountRateStorage_{s,r}})^{fy-y+1} - 1}{(1+\boldsymbol{DiscountRateStorage_{s,r}})^{\boldsymbol{OperationalLifeStorage_{s,r}}} - 1}\right) \quad \text{(SI8)}$$

The salvage value in the final year is then discounted back to the start year (SI9) and subtracted from the discounted investment costs to calculate the actual discounted storage cost (SI10).

$$\forall_{s,y,r}\text{: } DiscountedSalvageValueStorage_{s,y,r} = SalvageValueStorage_{s,y,r} / (1 + \boldsymbol{DiscountRateStorage_{s,r}})^{fy-sy+1} \quad \text{(SI9)}$$

$$\forall_{s,y,r}\text{: } TotalDiscountedStorageCost_{s,y,r} = DiscountedCapitalInvestmentStorage_{s,y,r} - DiscountedSalvageValueStorage_{s,y,r} \quad \text{(SI10)}$$

2.3.5.3 Integrating the Storage Additions into OSeMOSYS

As with the prioritisation of demand and demand shifting, the original objective function of the core model (OBJ) needs to be modified to allow for the inclusion of other than technology related costs (OBJ_rev). Equation (Acc4) does not need to be summed up over each technology any longer (Acc4_rev) and the total discounted costs (TDC1) are renamed to indicate that they just relate to costs of technologies (TDC1_rev).

$$minimise \sum_{y,r} TotalDiscountedCost_{y,r} \quad \text{(OBJ\_rev)}$$

$$\forall_{r}\text{: } ModelPeriodCostByRegion_{r} = \sum_{y} TotalDiscountedCost_{y,r} \quad \text{(Acc4\_rev)}$$

$$\forall_{s,y,r}\text{: } TotalDiscountedCostByTechnology_{y,t,r} = DiscountedOperatingCost_{y,t,r} + DiscountedCaptialInvestment_{y,t,r} + DiscountedTechnologyEmissionsPenalty_{y,t,r} - DiscountedSalvageValue_{y,t,r} \quad \text{(TDC1\_rev)}$$

This allows for a modified calculation of the total discounted costs, which adds the overall storage costs to the overall technology related costs (TDC2c).

$$\forall_{s,r}\text{: } TotalDiscountedCost_{y,r} = \sum_{t} TotalDiscountedCostByTechnology_{y,t,r} + \sum_{s} TotalDiscountedStorageCost_{s,y,r} \quad \text{(TDC2c)}$$

With this final step, the cost for every storage capacity increase will be minimised as part of the objective function.

2.3.6 Bringing It All Together

2.3.6.1 Integrating the Additional Demand Types

Equation (D3) defines the flexible demand for both, prioritisation of demand and demand shifting. Therefore, it only needs to be added once. The overall demand is defined as a standard demand as used in the core model, plus flexible demand types. The net charge of the assumed storage of the demand which may be shifted as well as the unmet demand are subtracted from the flexible demand. Conversion factors are used to convert the flexible demand back from seasons, day-types and daily time brackets to time slices (D1).

$$\forall_{y,l,f,r}: RateOfDemand_{y,l,f,r} = RateOfStandardDemand_{y,l,f,r} + \sum_{fdt,ls,ld,lh}\left(RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} - RateOfNetCharge_{fdt,y,ls,ld,lh,f,r} - RateOfUnmetDemand_{fdt,y,ls,ld,lh,f,r}\right) * \boldsymbol{Conversion_{l,ls}} * \boldsymbol{Conversion_{l,ld}} * \boldsymbol{Conversion_{l,lh}} \tag{D1}$$

The demand as defined in the core code of OSeMOSYS (EQ) is renamed to standard demand to differentiate it from flexible demand (EQ_rev = D2).

$$\forall_{y,l,f,r}: RateOfStandardDemand_{y,l,f,r} = \boldsymbol{SpecifiedAnnualStandardDemand_{y,f,r}} * \boldsymbol{SpecifiedAnnualStandardDemandProfile_{y,l,f,r}/YearSplit_{y,l}} \tag{EQ\_rev = D2}$$

2.3.6.2 Prioritisation vs. Demand Shifting

It is assumed that whatever is greater, the maximum share of the demand which may be shifted or the maximum share of the unmet demand, determines the minimum amount which has to be met instantly. Consequently, if the maximum share of unmet demand is larger than the share of demand which may be shifted, than the unmet plus the shifted demand has to be smaller than or equal to the maximum demand which could remain unmet (D4).

$\forall_{fdt,y,s,d,h,f,r}$:
$if\ \boldsymbol{MaxShareUnmetDemand_{y,fdt,f,r}} \geq \boldsymbol{MaxShareShiftedDemand_{y,fdt,f,r}}$:
$\boldsymbol{MaxShareUnmetDemand_{y,fdt,f,r}} * RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} \geq RateOfUnmetDemand_{fdt,y,ls,ld,lh,f,r} + RateOfNetCharge_{fdt,y,ls,ld,lh,f,r}$ (D4)

The other way round, if the maximum share of demand which may be shifted is larger than the maximum share of unmet demand, than the unmet plus the shifted demand has to be smaller than the maximum demand which may be shifted (D5).

$\forall_{fdt,y,s,d,h,f,r}$:
$if\ \boldsymbol{MaxShareUnmetDemand_{y,fdt,f,r}} < \boldsymbol{MaxShareShiftedDemand_{y,fdt,f,r}}$:
$\boldsymbol{MaxShareShiftedDemand_{y,fdt,f,r}} * RateOfDailyFlexibleDemand_{fdt,y,ls,ld,lh,f,r} \geq RateOfUnmetDemand_{fdt,y,ls,ld,lh,f,r} + RateOfNetCharge_{fdt,y,ls,ld,lh,f,r}$ (D5)

2.3.6.3 Integrating the Additional Costs

The original objective function of the core model (OBJ) needs to be modified to allow for the inclusion of other than technology related costs (OBJ_rev). Equation (Acc4) does not need to be summed up over each technology any longer (Acc4_rev), and the total discounted costs (TDC1) are renamed to indicate that they just relate to costs of technologies (TDC1_rev).

$minimise \sum_{y,r} TotalDiscountedCost_{y,r}$ (OBJ_rev)

$\forall_r$: $ModelPeriodCostByRegion_r = \sum_y TotalDiscountedCost_{y,r}$ (Acc4_rev)

$\forall_{s,y,r}$: $TotalDiscountedCostByTechnology_{y,t,r} = DiscountedOperatingCost_{y,t,r} + DiscountedCaptialInvestment_{y,t,r} + DiscountedTechnologyEmissionsPenalty_{y,t,r} - DiscountedSalvageValue_{y,t,r}$ (TDC1_rev)

This allows for a modified calculation of the total discounted costs, which adds the additional costs of not meeting demand, shifting demand and storing energy to the overall technology related costs (TDC2).

$\forall_{y,r}$: $TotalDiscountedCost_{y,r} = \sum_t TotalDiscountedCostByTechnology_{y,t,r} + \sum_{fdt} DiscountedCostOfUnmetDemand_{fdt,y,r} + \sum_{fdt} DiscountedCostOfShiftedDemand_{fdt,y,r} + \sum_s TotalDiscountedStorageCost_{s,y,r}$ (TDC2)

With this final step, all these costs will be minimised as part of the objective function.

2.4 Application

The following application serves to showcase the dynamics and enhanced functionality introduced through the code additions.

For the purpose of illustration, the electricity system of a fictitious town with the following characteristics is assessed. The local utility is assumed to purchase most of its electricity from the larger national grid at different prices for base and peak load supply. A small share of the supply is provided by the town's own PV installations. The town is assumed to have a constant overall demand, with the same daily load profile being applied throughout the modelling period (Fig. 6). The highest demand occurs during the morning and evening hours, with a lower demand during night time. The local utility would like to explore options to reduce its dependence on the national grid in a cost-effective manner by minimising expensive imports of peak generation.

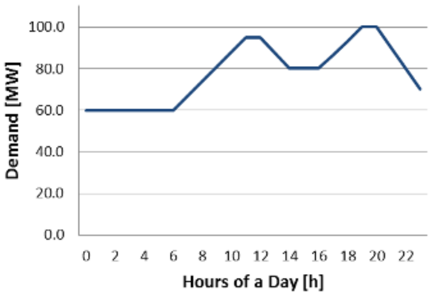

Fig. 6: Demand profile of standard day

The demand profile is assumed to remain constant over the modelling period 2011 to 2030 with a peak of 100 MW[124]. The town purchases up to 75 MW of base load at a levelised cost of 62.0 USD/MWh and whatever peak load is

[124] Demand was assumed to remain constant, as the optimisation of the overall generation capacity was chosen to be outside of the scope of this application. While being part of this enhanced version, optimising capacity additions is not new to OSeMOSYS and has already been described with the core code [101].

required at 85.8 USD/MWh[125]. Additionally, 20 MW of PV are available constantly from 8:00 to 20:00 at running costs of 30.0 USD/MWh[126] and with a yearly capacity factor of 20%. In this simplified model, seasonal fluctuations of PV availability have not been considered. A global discount rate of 5% was applied to all investments. Costs are based on values provided by the IEA [306]. While these values are derived from data from existing plants, it must be noted that the model was not set up to provide recommendations on specific Smart Grid options on a cost basis. It rather serves to demonstrate how such options can be modelled.

Based on these common assumptions, the subsequent scenarios describe resulting dynamics for each code addition. The final scenario then combines all code additions. Refer to Section 2.4.6 of Part A of this thesis for details with regard to the computational requirements of the individual model runs.

2.4.1 Variability in Generation

This code addition allows modelling capacity factors to be time dependent within a year. When modelling the fictitious town, this addition is required to ensure PV is only dispatched to generate electricity during the daytime[127]. All of the following examples include PV generation and build on this code addition. This example can therefore be considered as the reference scenario.

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125 Levelised costs are basically calculated as the sum of all discounted power plant related costs, including construction costs, divided by the total production during the lifetime of a power plant. Note that this does not include transmission and distribution costs. Base load was assumed to be generated by coal-fired power plants and peak load by gas-fired combined cycle turbines. For a more detailed definition of levelised costs and associated values refer to IEA et al. [306].

126 As all PV generation is assumed to be utility owned and investments happened in the past, it is dispatched by running costs. Peak and base load have to be bought from the national grid. Their price includes construction costs, as these costs have to be refinanced by the electricity provider.

127 Note that storage is not yet included at this stage.

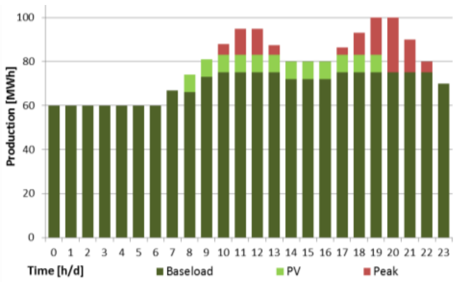

Fig. 7: Variability in Generation - Daily production in 2020

When adding this code block to the core code, OSeMOSYS calculates an overall discounted yearly system cost in 2020 of USD 26.5 million. Fig. 7 shows the generation mix throughout a day in that year. During the morning, afternoon and late evening hours, base load supply from the grid is not used to its theoretical maximum of 75 MW, as indicated by the dark green bars in Fig. 7. PV generation as shown in light green is always used when available. Expensive peak supply from the national grid as indicated in red is required during the morning and evening peak hours. Cumulatively over one day, it amounts to 109 MWh.

2.4.2 Prioritising Demand Types

In order to enable a prioritisation of demand types, a 'flexible demand' was introduced to the model. It was assumed that up to 10 MW of this demand may remain unmet throughout the day at an associated penalty to the local utility of 70 USD/MWh[128]. All other demand is considered to be of higher value and thus priority, and has to be met at the time it is demanded throughout the day.

Fig. 8 shows the results calculated by OSeMOSYS when adding this code block. The demand which may remain unmet is shown in light blue in Fig. 8a, with the continuous line indicating which demand is actually met by the model. The dashed line shows the original demand that was entered in the model. In Fig. 8b, the provision of expensive peak electricity as indicated in red is significantly

[128] The VoLL can actually be significantly higher if calculated by dividing Gross Value Added by electricity consumed in a sector. For the Republic of Ireland, it was 4 EUR/kWh for the industrial sector, 14 EUR/kWh for the commercial sector, and 24.6 EUR/kWh for households [293].

reduced between the hours 10:00 to 13:00 and 17:00 to 22:00. The base load grid supply as illustrated in dark green is dispatched as in the reference scenario. Overall, 96% of all demand is met, while the need for peak supply is reduced by 72% compared to the reference scenario.

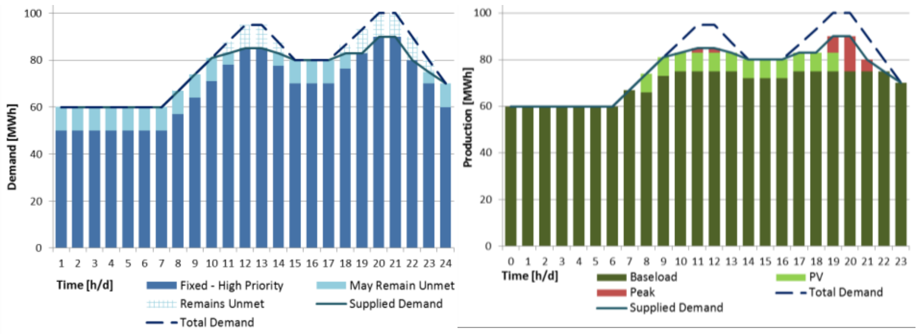

Fig. 8a+b: Prioritising Demand Types - Results for 2020
(a) Demand; (b) Production

2.4.3 Demand Shifting

In this scenario, a new flexible demand category was introduced. Up to 5 MW of this flexible demand category can be shifted +/- 1 hour at a cost of 10 USD/MWh/hour-shifted, with all flexible demand having to be met ultimately. All other demand was considered fixed and has to be met at the time it is demanded throughout the day. Note that unlike in the previous case, no demand may be left unmet.

The demand for electricity which may be shifted is shown in green in Fig. 9a. The continuous blue line on the top indicates the new demand profile after OSeMOSYS shifted some of the loads, while the dashed line shows again the original demand as entered into the model (blue plus green bars). The lines close to the x-axis indicate which loads have been met in advance (black line) or delayed (orange line), compared to the original profile. Negative values indicate periods when loads were reduced, i.e., the initial demand was 'shifted' away from these periods. Positive values indicate when loads were increased, i.e., these are the periods in which additional electricity was provided to meet shifted demand.

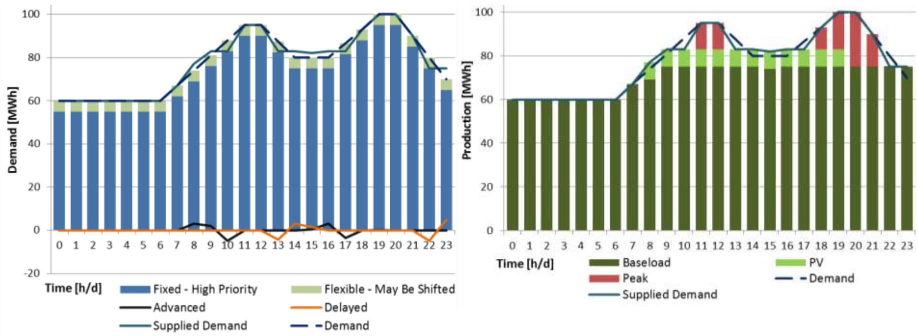

Fig. 9a+b: Demand Shifting - Results for 2020
(a) Demand; (b) Production

By way of illustration, some of the flexible demand is not met during hour 13:00, as the blue line cuts into the green bars during that hour. The orange line has an associated negative value during this time, indicating that the demand will not be met then, but shifted to a later period. Similarly, demand is shifted from hour 22:00 to 23:00. Equivalently, demand is shifted at hour 10:00 as well as 17:00 to be met earlier. This is indicated by the black line.

Fig. 9b shows that this flexibility allows using almost all available base load from hour 09:00 to 23:00 (dark green bars), while drawing on PV whenever it is available (light green bars). This helps reduce the need for peak supply (shown in red) by 16% as compared to the reference scenario[129].

[129] Note that the available peak capacity is not reduced, as peak electricity is simply bought from the larger national grid without any capacity constraints. In this model there is a cost reduction associated with reducing peak generation (i.e., the cumulative length of the red bars in Fig. 9b), but not peak capacity. If the local utility would have had to invest in new local capacity additions, peak capacity would have been a cost factor and the model would have used the available flexibility to minimise such capacity additions.

2.4.4 Storage

In order to demonstrate the functionality provided by the storage code addition, all PV generation was assumed to be connected to batteries with an efficiency of 90% and a capacity of 10 MWh.

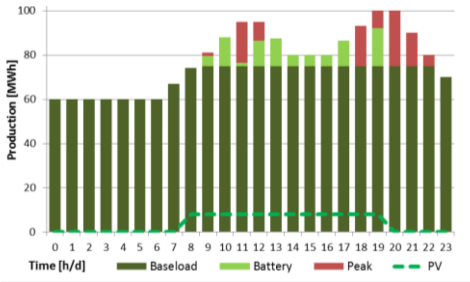

Fig. 10: Storage - Daily demand in 2020

Fig. 10 indicates the base and peak load supply from the national grid, as well as battery use and PV generation by the local utility. PV is used to its maximum capacity throughout the day (dashed line) and so is base load from hour 9:00 to 22:00. As indicated by comparing the dashed line to the light green bars, not all of the PV electricity generated during the hours 8:00, 11:00, 14:00, 15:00, 16:00 and 18:00 is used immediately. Such electricity is stored in batteries to be discharged during the morning and evening peak. This reduces the need for peak supply from the national grid (red bars)[130] by 9% as compared to the reference scenario.

2.4.5 Bringing It All Together

Finally, in this last application all code additions are brought together simultaneously. The bars in the graph on the left of Fig. 11 indicate how demand is split up: 10 MW of demand may remain unmet (light blue), up to 5 MW may be shifted +/- 1 h (green) and the remaining demand has to be met

[130] Note that the model does not take into account at what time peak generation is reduced, as this does not affect overall costs. This leads to, e.g., high peak generation at hour 18:00 and reduced peak generation in the following hour. However, the other way round would be an equally valid solution for the model.

instantaneously (dark blue). As in the previous code addition, all PV is connected to 10 MWh of storage.

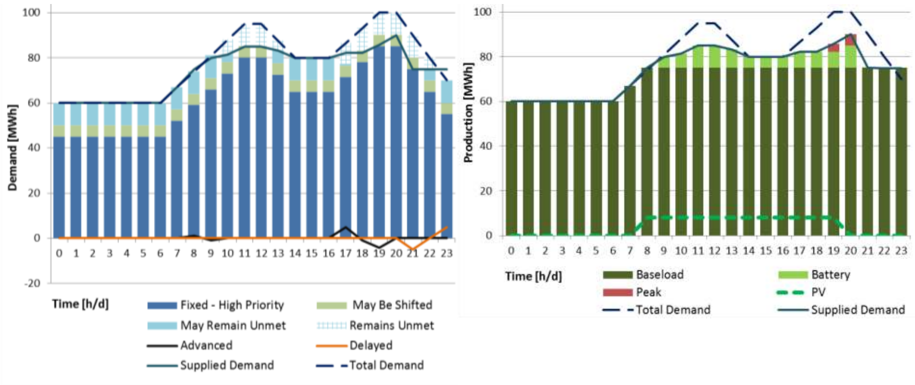

Fig. 11a+b: Bringing It All Together - Results for 2020
(a) Demand; (b) Production

The continuous blue line in Fig. 11 indicates how electricity is supplied by OSeMOSYS after utilizing all the flexibility the system provides. The light blue bars in Fig. 11a show the demand which may remain unmet. The hatched fraction of these bars is demand which the model decided not to meet. For example, during the hours 18:00 to 21:00 none of the light blue demand is met (all light blue bars are hatched). At the hour 20:00 no demand is shifted, as the dark blue line is identical with the dark blue plus the green bar, and both the orange and the black line are zero. At the hour 21:00, however, some of the green demand is shifted (the dark blue line is below the green bar) to be met later (orange line has an associated negative value).

Fig. 11b shows that PV is used to its maximum capacity (dashed green line). Not all PV generation is used immediately. For example, at hour 8:00 all electricity from PV is used to charge the batteries, which are then discharged later (light green bars). During the hours 8:00 to 23:00 as much base load generation (dark green bars) as available is used. Almost no peak load supply from the national grid (red bars) is required. It was reduced by 92% as compared to the reference scenario, while 96% of the overall demand (dashed blue line) is still met.

2.4.6 Computational Requirements

Table 3 provides an overview of the computational requirements of the individual model runs. In the underlying core version as of 8 November 2011, the core code of OSeMOSYS was characterised by the creation of rather large matrices. This was due to the structure of the code and its flexible use of the element 'technology'. A technology allows the combination of any input fuels to produce any combination of output fuels. Therefore, equations were set up when running the model to exclude input and output fuels which are unrelated to a specific technology. This was required to define, for example, that a wind power plant in OSeMOSYS does not consume coal and does not produce heat. The advantage of this flexible use of the element 'technology' is the simplified code formulation with easier readability.

However, as the model size increases, the open source solver GLPK may require more memory than available. GLPK is known to be less efficient in handling memory than commercial solvers like CPLEX. Therefore, currently two versions of OSeMOSYS are being maintained. One extended version which focuses on easy readability and another version which was developed with the aim to improve performance. The applications presented in this thesis all draw on the extended version of OSeMOSYS due to its easier readability.

All models were run under Windows 7 Enterprise, 64-bit, on a machine with 8 GB of RAM and a 2.5 GHz Intel Core i5-2520M CPU.

Table 3
Computational Requirements of Individual Model Runs

Model Run	Matrix Size		Memory Used (in Megabytes)	Running Time (in Seconds)	
	Initial	After Pre-processing		Optimisation	Total*
Variability in Generation	115,260 x 112,908	16,804 x 14,255	153.4	3.4	6.4
Prioritising Demand Types	128,135 x 125,783	18,004 x 16,055	172.1	3.9	8.7
Demand Shifting	149,885 x 143,933	24,297 x 21,196	236.9	6.6	17.0
Storage	124,010 x 115,683	22,324 x 17,751	164.9	11.1	14.7
Getting It All Together	169,660 x 154,133	30,492 x 25,967	262.1	12.4	24.3

*The total running time includes the matrix generation, pre-processing, optimisation and writing of the output file.

2.5 Conclusion

A standard energy modelling methodology based on cost minimisation was extended by capturing selected attributes associated with Smart Grid advances. Specifically, the utility and ease-of-use of OSeMOSYS was demonstrated by modifying the code to improve its functionality. Methods to integrate selected features of Smart Grids in energy system models were presented and key dynamics based on a simple application were showcased.

The flexible technology definition of the core code of OSeMOSYS allows the analyst to go far beyond this specific set up. A range of additional Smart Grid options and practices can be modelled, which all may compete against each other to minimise the cost for society under various constraints and realities.

For example, an electric or gas boiler may compete against a heat pump and co-generation to meet a district heating demand[131]. At the same time, the model might be set up to investigate if increased variability in generation is best balanced by an investment in a future hydropower reservoir or by hydrogen storage to power fuel cell cars. Peak demand may be reduced by shifting certain demand types within predefined intervals at costs increasing with the delay of meeting this demand. Further, high electricity prices may force some consumers to reduce their electricity consumption. Overall, the model will choose among all competing options and, assuming 'perfect competition' between all technologies, will invest only in those which are most economically efficient.

However, the expansions presented in Part A of this thesis cover but a subset of issues related to Smart Grids and have been modelled using well-known linear programming methods. They do not attempt to address a full suite of other important modelling tasks, which may be the focus of future work. For example, these could include assessments of the role of Smart Grids in frequency and voltage control [281,308], or tackling 'perfect foresight' limitations [95].

Further work will include a detailed appraisal of an array of Smart Grid technology options based both on the presented energy modelling methodology as well as potential future code improvements. Case studies may also help assess the value of the increased system flexibility Smart Grids could provide over the next decades.

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131 Refer to Haichao et al. [307] for a spatial modelling approach of a district heating systems' atmospheric environmental impacts.

A specific area of interest is to model how Smart Grid advances may contribute to the accelerated provision of key energy services to the poor. Examples include assessing the social efficacy of subsidies targeting specific services, rather than electricity, or modelling trade-offs associated with low-cost tariffs versus reduced reliability. Other focus areas of broad interest would include integrating variable and inflexible base load generation options in longer term energy system expansion plans [309].

Future applications and comparative assessments will help determine the value of the incremental OSeMOSYS enhancements presented in Part A of this thesis. In any case, OSeMOSYS has proven to be a useful tool to quickly test out new code additions enhancing integration between supply and demand. Therefore, it may be useful as a test-bed for new functionality in tools with wide-spread use and larger applications, such as MESSAGE, TIMES, MARKAL or LEAP.

Like the applied core code in its version as of 8 November 2011, the functional blocks described in this section are available in the public domain and in Annex C. The modelling of storage was first integrated into a beta version of OSeMOSYS dated 1 June 2012. As of 14 March 2013, it is integrated into the core code of OSeMOSYS in the exact same form as presented in this thesis [310].

Part B
Integration Between Timeframes

In 2012, renewable energy sources contributed 70% of total capacity additions in the European Union. As the shares of variable renewable generation in power systems increase, so does the need for, *inter alia*, flexible balancing mechanisms. These mechanisms help ensure the reliable operation of the electricity system by compensating fluctuations in supply or demand. Operational power system models are frequently applied to assess the implications of short-term variability of supply and demand. However, this level of analytical granularity is commonly omitted in the long-term energy models used to investigate future capacity investments.

Part B assesses OSeMOSYS' ability to partially bridge the gap between these two families of models and the timeframes they cover. Specifically, it presents an approach to consider the contribution of wind power installations to the system adequacy. Further, OSeMOSYS was extended to model operating reserve capacities required for balancing services. The dynamics introduced through these model enhancements are presented in a test case application, which serves as a proof-of-concept. Dispatch improvements and implications on capacity expansions were further quantified using an Irish case study.

Section 1 provides the rationale for the need for integration between timeframes, specifies the scope, defines the term flexibility and assesses the resulting key implications for energy system models. Section 2 presents metrics to derive the capacity credit of wind and short-term balancing requirements, and outlines their implementation within OSeMOSYS. Section 3 details this implementation by providing conceptual descriptions linked to the algebraic formulations. Section 4 presents a test case application of the model enhancements. Section 5 describes the Ireland case study and discusses the achieved improvements before Part B concludes in Section 6. Annex D provides the code of the model enhancements. Annex E presents detailed assumptions applied in the test case and Annex F code adjustments to model Ireland's pumped storage hydropower plant.

1 Short-term Variability and Long-term Outlooks

1.1 Rationale

Ensuring a cleaner supply of energy drawing on locally available renewable energy resources has become a key policy objective for many countries. According to the IEA's New Policies Scenario, renewable electricity generation will almost triple in the period to 2035, and contribute over 30% to total power generation [1]. Many announced national and regional policy goals promote even higher shares [311,312]. Related modelling demonstrates the feasibility and benefits of integrating large shares of renewable supply into power systems [45,313,314].

In Europe, related ambitions are largely driven by the commitment to comply with EU legislation and its 20% renewable energy target up until 2020 [315]. In the year 2000, renewable sources in the EU accounted for 21% of all new capacity additions [316]. This value increased to 70% in 2012. It is likely to remain high in the coming decades as the EU intends to reduce greenhouse gas emissions until 2050 by 80% – 95% below 1990 levels [311].

The growing reliance on renewable power sources may result in significant instantaneous shares of the generation from such sources. As an example, in order to meet the Republic of Ireland's 16% renewable energy target, and due to a heavy reliance on the decarbonisation of the power sector, the grid may need to be adapted to accommodate maximum wind penetration rates of 60 – 80% of the load [317].

Balancing the variable output of such levels of renewable electricity generation requires a high degree of flexibility in the power system[132]. Increasingly, power

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[132] The term flexibility is applied in this thesis as "… the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise. In other words, it expresses the capability of a power system to maintain reliable supply in the face of rapid and large imbalances, whatever the cause. It is measured in terms of megawatts (MW) available for ramping up and down, over time." [318].

plants or demand-side options have to be available as ‘operating reserve’, i.e., they have to be able to quickly adjust their generation or demand if needed[133] [319]. This is required to limit and counterbalance any mismatches between demand and supply and curb deviations from the power system’s design frequency to guarantee *system security* [281]. System security refers to the ability of a power system to dynamically respond to disturbances from within the system [320]. Further, rising shares of variable generation are generally associated with a diminished contribution to the power *system’s adequacy* per unit of variable generation capacity [90,321]. System adequacy refers to the availability of infrastructure to meet demand throughout the year under steady state conditions [320].

Power system issues associated with variable renewable generation are well documented (e.g., in Hand et al. [45], IEA [318,322] and UKERC [323]). Flexibility requirements are nothing new to power systems, yet, their importance in this new context is providing an impetus for their prioritisation in market design and expansion [324]. Several supportive families of modelling tools exist which serve to gain insights on how this can best be done. They can be distinguished by their scope and the timeframe they cover.

When assessing how future energy systems might look like several decades ahead, long-term energy system models such as LEAP, TIMES or MESSAGE have proven their value. Connolly et al. [81] and Ludig et al. [325] present further tools with a focus on the integration of renewables. However, given their long-term focus, commonly applied modelling approaches usually do not focus on the short time scales associated with system security issues. According to Deane et al. [49] and as confirmed by the applications presented in Part B of this thesis, they may therefore inadequately represent the need for increased power system flexibility. This results in sub-optimal power plant dispatch and investment decisions.

The reason why short-time operational issues are often omitted is that long-term models usually do not provide a high temporal resolution. Further, the penetration-rate dependent contribution of renewable electricity generation to system adequacy is commonly not implicitly considered within the model. Subsequently, medium- to long-term energy models may misrepresent the investment implications of ensuring system adequacy and security.

[133] Refer to Section 1.3 in Part B of this thesis for further definitions of operating reserve and metrics to capture their scale.

A separate suite of electricity market simulation models and operational power system tools is specifically designed to investigate these issues. Tools like GTMax [43], PLEXOS [44] and Grid View [45] entail a much higher temporal resolution and cover numerous operational constraints related to unit commitment and dispatch. Therefore, they enable the most accurate consideration of flexibility requirements within the electricity sector, although each has a specific temporal focus and system boundary. Further examples of such tools are presented in Foley et al. [36]. However, these tools commonly exclude non-electricity sectors like heat or transport, or tend to focus on operational aspects of existing power systems [83,87,326]. They might therefore only provide limited insights on the design of future energy systems.

Related improvements of energy system models[134] need to try to match their long time horizon and holistic energy systems focus with sufficient detail on the power sector. Those operational aspects which influence longer term investments need to be considered. The increasing flexibility that power systems will need to provide requires a better representation in the applied energy models. Flexible and open source models may constitute useful tools to test out such refinements [31].

1.2 Scope

Part B of this thesis demonstrates the need for increased flexibility considerations in long-term energy system models in order to more adequately assess future capacity expansions. Its main focus is to highlight this need and to show how this can be implemented, as opposed to detailed investigations into effective market designs in support of increasing shares of renewable electricity generation.

OSeMOSYS was extended by incorporating an approach to model the contribution of wind power towards system adequacy as penetration rates rise [51]. Further, the model was extended to assess upward and downward reserve requirements across two timeframes, based on minimum stable operation levels, ramping capabilities and cycling characteristics. Upward reserve refers to the ability to increase generation to compensate outages or unexpected

[134] For the sake of simplicity, the term 'energy system models' is used to refer to models covering a medium- to long-term timeframe, if not stated otherwise.

demand increases. Downward reserve is the ability to reduce generation to compensate unexpected reductions in demand or increases in (renewable) power output [327].

A key focus of the enhancements was to ensure their general applicability to various countries or regions. Care was taken to limit the amount of additional input data required, with the option to enhance the model accordingly if such data is available.

The model extensions are first applied drawing on a test case application. Various OSeMOSYS models with various levels of detail were compared to each other to identify how results are affected by the extensions. After this proof-of-concept, OSeMOSYS models were set up for Ireland and compared to preceding work by the University College Cork (UCC) [49]. In that work, a long-term energy system model (TIMES) was soft-linked with a unit-commitment and dispatch model of the Irish power system (PLEXOS). Given the more detailed temporal resolution and representation of technical characteristics in the soft-linked TIMES-PLEXOS approach, its modelling results provide for an improved dispatch. Therefore, they serve as a benchmark for the OSeMOSYS models.

1.3 The Need for Flexibility

Depending on the timeframe of focus, the term flexibility in energy systems has different implications on system operation and investments. According to the IEA [183], flexibility in electricity systems is categorised as: stability services, covering a timeframe of seconds; adequacy services to ensure demand is met over the course of several months to years; and balancing services for the timeframe in between.

In contrast, according to the European Network of Transmission System Operators for Electricity (ENTSO-E) [328] the term 'balancing' includes everything after 'gate closure'[135], i.e., market closure, which requires actions by the system operator (SO). Balancing includes ancillary services to guarantee system security such as the provision of black start capability and reactive power as well as demand response measures [328]. The term balancing is however defined differently in the Nordic electricity market, which differentiates between

[135] As opposed to 'scheduling'.

balance planning on the day-ahead and intra-day market by balance responsible market players, and *balance regulation*, which is performed by the transmission system operator during the hour of operation [329].

Especially for short-term balancing services, various additional denominations exist and the same term might entail different technical requirements in different countries. Often used market-specific terms include: frequency response, fast reserve, spinning reserve, regulating reserve, contingency reserve, disturbance reserve, replacement reserve, etc. [323,327,328,330–332]. The terminology used in a given context is largely influenced by national market structures, grid codes and the perspective of the author. Commonly, three types of operating reserves are distinguished [332]:

- Grid stability services are provided by what is called the *primary reserve* or *response*. This type of reserve is locally automated and reacts to deviations to the nominal system frequency.
- *Secondary reserve* is usually automated centrally and serves to release the primary reserve for future operation and restore the system's frequency.
- Finally, the *tertiary reserve* is activated manually and has an activation time of up to one hour[136].

While the timeframes associated with these reserves vary, primary control reserve can commonly be activated within 30 seconds while secondary and tertiary control reserves have to be fully available within 5 – 15 minutes [332].

Primary reserve may be provided by pumped storage and part-loaded thermal power plants, like nuclear power [334]. Some of these plants may, for example, operate close to the mid-point of their operating range in order to maximise the reserve services they provide [330]. This allows them to ramp up or down quickly over their available operating capacity range. However, it typically comes with associated efficiency losses of 10% – 20% and beyond for thermal power plants [335]. Sometimes, primary reserve may as well be provided by wind parks, even though with less demanding requirements.

In addition to part-loaded plants, secondary and tertiary reserves may draw on plants which can quickly synchronise with the grid. This may including

[136] As mentioned, these categorisations differ between countries. For example, tertiary reserve is not referred to in the Nordic system [333].

hydropower connected to reservoirs, open cycle gas turbines and to a lesser extent diesel generators as well as potentially future improved technologies like direct injected coal engines [330,334,335].

Apart from power plants, reserve services may as well be provided by demand response measures facilitated through Smart Grids, and load shedding. Responsive load can be automated and faster than supply-side options, as usually no ramping rates apply [336]. Further options include the curtailment of power output, enhanced balancing areas (e.g., through cross-border trade, virtual power plants, or the integration of distributed thermal generation), storage (e.g., electric vehicles or compressed air storage), or conversion to other energy sources (hydrogen generation, heat pumps) [40,190,335,337]. Ancillary markets for the trading of reserve services may help ensure that these options compete against each other to provide reserve at the lowest marginal cost.

The extent of short-term balancing services is expected to increase significantly over time, especially if more stringent climate change goals should be realised [183]. Ensuring adequacy requires a 'system reserve margin' on top of this, i.e., capacities in addition to those needed for meeting peak demand. This reserve margin accounts for (scheduled) outages of grid infrastructure and power plants.

1.4 Key Implications for Energy Systems Models

1.4.1 Temporal Resolution

Long-term energy system models mostly focus on system adequacy. Commonly, they do not attempt to consecutively model all days or hours within a year [49]. This is to a large extent due to their long-term time horizon and the computational power, time and data required for increasing temporal resolution. Assessing the daily dispatch in detail might also create a false precision compared to the overall uncertainties associated with long-term projections.

Long-term energy system models are commonly set up using time slices, i.e., representative time periods within a year (refer to Section 2.2 in Part A for further explanations). While such models might be based on as little as one single yearly time slice [338], more commonly six to twelve time slices are applied [26,339]. An example for the latter is the model used to inform the IEA's Energy Technology Perspectives report [183].

Several models provide a more detailed temporal resolution. For example, Howells et al. [340] based their model on 24 time slices per year. Nelson et al. [50] further increased the temporal resolution to 144 time slices per four-year investment period. Pina et al. [341] and Kannan and Turton [342] all used 288 time slices per year.

This increased number of time slices can enable a more accurate representation of variable renewable energy resources. However, it is still not sufficient to adequately consider issues such as unit commitment, start-up costs, minimum down times or forced outages. Instead from a technical point of view, the dispatch is only constrained by an exogenously defined maximum availability of the technology and its fuel supply within each time slice [342].

Historically, the obtained results with a lower temporal resolution were often deemed sufficient for informing policy development and, in some cases, capacity expansion planning. An appropriate depiction of the daily dispatch was not – and still is not – a focus of such models[137]. Further, lower variable generation levels required less short-term balancing. Systems with certain types of power plants, e.g., dispatchable hydropower, might have inherently been able to meet most reserve requirements, despite the lack of explicit flexibility considerations within the models.

1.4.2 Reliability Considerations

With increasing rates of variable electricity generation there is a need to revisit these simplifications. An exhaustive review of international studies indicates that additional operating reserve capacities of 2% – 9% of the installed generation capacity of variable sources are required at penetration levels between 10% – 20% [323]. A more recent comparison by Holttinen et al. [343] provides a similar picture. Further, the range of capacity credits attributed to variable generation reduces significantly as penetration levels increase [343]. The capacity credit is one measure of the contribution of a technology to the reliability of the power system [344]. Several definitions and calculation methods exist [90,330,345,346]. Commonly, but not exclusively, the capacity credit relates to the impact of a new power plant on the LOLP.

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[137] However, sometimes they were combined with short-term models to allow for a more robust output. Refer to Section 1.4.3 in Part B for an example.

Given these implications for operating reserve requirements and the capacity credit, maintaining system reliability becomes a key concern as renewable energy generation rates increase. However, medium- to long-term models mostly do not enable sophisticated reliability assessments. Rather, a simple metric is applied by allowing to enter a ‘system reserve margin’ as an input parameter. This system margin ensures that the capacity credit of all power plants within the system always exceeds the load by a certain percentage. The value of this margin depends on reliability requirements, which may be affected by market design and operations. Further, the capacity credit is commonly defined as an input value and not calculated within the model as a function of renewable generation penetration rates. Subsequently, such medium- to long-term energy models may misrepresent the investment implications of maintaining system reliability.

In some modelling applications, the dependence of the capacity credit on penetration rates is well reflected. For example, in the UK MARKAL model, different capacity credits are assigned to different ranges of variable generation capacities. These are based on external calculations with the Wien Automatic System Planning programme (WASP) [80,347]. In the U.S.-focused Regional Energy Deployment System (ReEDS), the capacity credit of renewable energy generation is calculated for each of the 17 yearly time periods considered within the model [321]. This draws on exogenously defined Pearson correlations between outputs of pairs of plant sites.

However, the required extensive time-series data or results from reliability assessments might not always be available. In such cases, the capacity credit might be derived from approximations based on the capacity factor, i.e., the ratio of the average output to the total output over a specified time period [91]. But even in this case at least some time-series data might be required to capture its seasonal and diurnal variations [348], for example if the capacity credit is calculated as the capacity factor over peak periods. Such approximations do not capture several aspects of detailed reliability assessments, including the sizes of the various plants in the power system and their reliability. The system adequacy might therefore not be insured.

Also, unpredictable variations are rarely depicted in medium- to long-term models. Yet, they are a key driver for system costs associated with balancing. Thus, system security cannot be guaranteed when using such models. Taking related short-term operational issues into account usually requires the use of separate electricity dispatch models. However, these short-term, operational power system models provide limited insights for capacity expansion planning.

1.4.3 Linking Long-term with Short-term Models

The gap between the suites of long-term energy systems and operational power system models is well recognised [341]. Sometimes, it is addressed by interlinking two modelling tools: a long-term model is used to derive future power plant capacity mixes and a power system model for the load dispatch [29,45–50]. For example, Chaudry et al. [25] covered short-term fluctuations by interlinking an energy system model of the UK with a power system model based on probabilistic production cost simulations, and with a geographical infrastructure investment model. This approach allowed the consideration of some aspects of system reliability. However, it did not take specific ramping characteristics of various generation technologies into account.

While long-term capacity investments can easily be fed into short-term models, the information flow back to the long-term model appears to be more challenging and is sometimes ignored. In any case, the operational detail as captured by the power system model is not part of the optimisation of the long-term capacity expansions when using two separate tools. The consequence may be long-term investment strategies which are economically sub-optimal. Further, setting up two independent models requires expertise in two different modelling tools and may involve collaboration between different research groups. The level of effort to set up independent models might be a deterrent to a more frequent application. In addition, due to overlapping but different sets of input parameters of each of these tools, an inherent risk of hidden input data inconsistencies arises.

An approach may therefore be useful which allows drawing on the advantages of long-term models with a lower temporal resolution, but without ignoring the main dynamics introduced by variable generation. For example, Ludig et al. [325] considered short-term fluctuations in a generic way. This was done by specifying technologies which have to be available to cover the largest observed drop in renewable energy output over a short time horizon.

Sullivan et al. [338] extended a MESSAGE model based on a single time slice by introducing flexibility coefficients, which specify the share of flexible generation provided or required when dispatching a technology or meeting a load. The flexibility coefficients were determined through a parallel analysis based on an NREL unit-commitment model with an hourly resolution.

In the ReEDS long-term energy model, upward reserve requirements across one timeframe are considered within a single power system model of the U.S. [45]. In this multi-regional modelling tool, designated power plants were allowed to operate in between their minimum operating level and their maximum seasonal output to meet reserve requirements. As in the models developed by Chaudry et al. [25], ramping characteristics of various generation technologies were not explicitly considered. In NREL's Renewable Electricity Futures Study, the ReEDS model was therefore interlinked with a separate, hourly electricity dispatch model to analyse one year in more detail [45].

2 Extending OSeMOSYS

OSeMOSYS was chosen as a useful tool to consider flexibility in energy systems within one single model, both given its open source nature and its clear and concise code [39,101]. OSeMOSYS was extended in a generic fashion to ensure its wide applicability with limited additional input data requirements. Refer to Section 5.1 of the introduction of this thesis for further background on OSeMOSYS.

Sections 2.1 and 2.2 of Part B of this thesis outline how the capacity credit of wind power generation and operating reserve requirements were considered in OSeMOSYS. Each section starts with a general introduction to the approach and provides a concise outline of the implementation in OSeMOSYS. Both sections end with a discussion of the limitations of the chosen approach. The conceptual description and algebraic formulations of the implementation is provided in Section 3 and the final code implementation in Annex D.

2.1 Capacity Credit of Wind

2.1.1 An Approximation Based on Penetration Levels

Voorspools and D'haeseleer [51] derived an analytical formula which provides a first estimate of the capacity credit of wind power. While this formula might not match the accuracy of more detailed wind integration analysis, it provides a useful tool in view of a lack of extensive time-series data or external reliability assessments. Its implementation within OSeMOSYS is therefore exemplary and can easily be replaced by more detailed, country-specific assessments if available.

In the analytical formula, the capacity credit is calculated as a function of penetration levels, the annual capacity factor, the reliability of conventional plants and the dispersion coefficient. This coefficient serves to represent the geographic smoothing effect of the variability of wind [343]. Note that in these equations the wind penetration rate is defined as the installed wind power per peak load. This leads to a much higher rate than a comparison of electricity from wind power to the total generation.

The formula was empirically fitted to represent probabilistic capacity credit calculations performed for the Dutch territory by Van Wijk [349]. They were then extended to cover a range of different dispersions of wind power plants, drawing on capacity credit calculations by the Irish TSO and by Martin and Carlin [350] for Western Australia [351] (Fig. 12). The approach was verified by a comparison with results from a further literature survey. The derived formulas (Eq1 & Eq2) use a capacity credit definition based on a comparison with a conventional system excluding wind (Eq3). It will therefore lead to a higher capacity credit as opposed to definitions based on 100% reliable units [90].

$$CapacityCredit(x) = \frac{32.8}{0.306+\delta}\frac{CF_{wind}}{R_{system}}\left(1+3.26*\delta e^{-0.1077(0.306+\delta)*(x-1)}\right) for\ x > 1\% \quad \text{(Eq1)}$$

$$CapacityCredit(x) = CapacityCredit(x=1)\ for\ x < 1\% \quad \text{(Eq2)}$$

$$CapacityCredit = 1 - \frac{P_{with} - P_{without}}{P_{wind}} \quad \text{(Eq3)}$$

Note that (Eq2) was reformulated to ensure it result in the same value as (Eq1) for a penetration rate of 1%, in line with the description of the formula by Voorspools and D'haeseleer.

CapacityCredit:	Capacity credit in % of installed rated wind power
x:	Penetration level; installed wind power as % of peak load
CF_{wind}:	Annual capacity factor of wind project in %
R_{system}:	Reliability of conventional plants in %
δ:	Dispersion coefficient; equals 0 for perfect spread and 1 for no spread
P_{wind}:	Additional wind power capacity
P_{with}:	Total power system capacity including P_{wind}
$P_{without}$:	Total capacity of a power system excluding P_{wind}, but with the same LOLE as the system including P_{wind}
LOLE	Time period during which the load exceeds the supplied power [352]

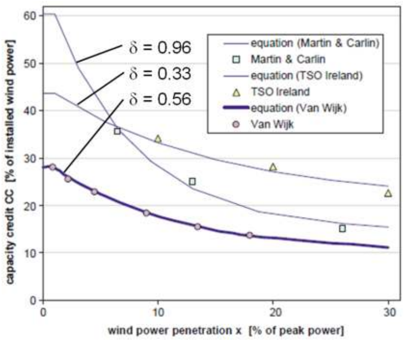

Fig. 12: Comparison of analytical formula with results from the literature, as adapted from Voorspools and D'haeseleer [51]

According to Voorspools and D'haeseleer [51], a typical values for the reliability of conventional plants is 85%, while dispersion coefficients range from 0.30 for wind parks spread across Europe to 0.33 for Ireland, 0.56 for Denmark, 0.60 for the Tri-State territory in Nebraska, USA, and up until 0.90 to 0.96 for single units. The capacity factor of wind power plants roughly ranges from 20% to 40% with a median value of 26% according to the IEA [306]. This corresponds to the average value for the U.S. according to Boccard [353], who mentions an average value of 21% for the first 15 countries who joined the EU.

In OSeMOSYS, the formulas (Eq1) and (Eq2) have been implemented for each modelling region as a piece-wise linear approximation. Refer to Section 3.2 of Part B of this thesis for further details. Note that penetration rate dependent capacity credits for other variable technologies such as solar power follow a similar curve [354]. Given the availability of external assessments, they could therefore be implemented in OSeMOSYS drawing on a similar piece-wise linear approximation.

2.1.2 Limitations

The implemented capacity credit calculations present a significant improvement as compared to its approximation as a constant. However, the main limitation of the analytical formula by Voorspools and D'haeseleer [51] is the required selection of a dispersion coefficient, which strongly influences the results. This is as well visible in the shape of the curves in Fig. 12: no spread (δ = 0.96) results in a very steep curve. An improved spread decreases the slope. A perfect spread with no correlation between individual wind power plants ($\delta = 0$) would result in a horizontal line.

When comparing the practical values of wind parks as mentioned in the previous section with each other, dispersion coefficients for wind parks vary between 0.30 – 0.60. These differences may not seem obvious and were apparently adjusted to match the values derived from the literature review (Fig. 12). Therefore, the impact of these variations in the dispersion coefficients were assessed for a system with a wind power capacity factor of 30%, a penetration rate of 20% and an overall reliability of 85%. Varying the coefficient from δ = 0.3 – 0.6 led to an 8% higher capacity credit for the lower coefficient. If an average value of $\delta = 0.45$ is chosen, the error may therefore be estimated to be within +- 4%.

The assessed variations in the dispersion coefficient just serve as an indication of its impact on the results. Voorspools and D'haeseleer compared results from the analytical formula with individual capacity credit values mentioned in the literature. However, assessing the accuracy of the analytical formula would require a comparison with various detailed reliability assessments across a range of penetration rates.

Apart from the choice of the dispersion coefficient, another limitation of the formula is that it does not cover any country specific correlation between peak demand and wind generation. For example, in the UK, the capacity factor of wind power during peak demand periods was found to be around 30% higher than the annual average [355]. For such a positive correlation, a higher capacity credit of wind power can be expected.

Further, penetration rates up to 30% were considered when designing this formula. Higher penetration rates may therefore be beyond its range of validity. In addition to the penetration rate, the Loss of Load Expectation (LOLE) of a power system has a strong influence on the capacity credit, which tends to be higher in more unreliable power systems [90]. As this formula was derived from calculations focusing on countries with very reliable electricity systems, special attention is required when applying it to, for example, developing countries.

Given these limitations, this formula might benefit from calibrations with more detailed reliability assessments based on empirical and probabilistic methods. But even without these, it constitutes a convenient tool for preliminary assessments of dynamics which may have been neglected otherwise. Further, the limited input data required enables quick sensitivity analysis, e.g., with different penetration rates.

2.2 Balancing

2.2.1 Capturing Reserve Requirements

Reserve requirements for short-term balancing are country specific and depend on the market design [332]. For example, a gate closure shortly before the actual dispatch will result in lower reserve requirements due to an increased forecasting accuracy [87]. While the calculations applied by system operators to determine their amount could be directly integrated into an energy model, this might not be the best approach. First, they are largely based on experiences with present power systems and markets. Therefore, they might not depict future requirements appropriately. Second, these calculations only define system operator requirements and do not include any balancing within a utilities own portfolio. As such, if implemented in an energy system model, they may result in insufficient provision of reserve. Detailed reliability assessments would provide a solid basis for forecasting balancing requirements. However, they go beyond the scope of commonly used long-term models.

Some generic key metrics regarding the composition and scale of reserve requirements can be derived from the literature. A frequently applied approach is the use of the standard deviation σ of unpredictable variations of supply and demand. Often, between +-2σ and, commonly, +-3σ is applied to estimate reserve requirements [323,330,356]. If a normal distribution of unpredictable supply and demand variations is assumed, +-3 σ would cover 99.7% of all of possible system states [357]. The total reserve requirements may be calculated as three times the sum of the root-mean-square of the standard deviations of demand and generation, i.e., $3 * \sqrt{\sigma_D^2 + \sigma_S^2}$. Note that this formula assumes no statistical correlation between the different errors, which might not always be the case in reality [358]. Further, the loss of the single largest unit (N-1 approach, refer to Section 1.2.3 of Part A) may be considered, as it is done in the UK or France [323,332]. A more appropriate, but also more complex probabilistic approach to consider outages is described by Doherty and O'Malley [359,360].

ILEX in association with Strbac [361] suggest a simplified approach to assess reserve requirements: Fluctuations above four hours are expected to be met by bringing any available power plant type online. Until these plants are online, all variations have to be covered by secondary (and tertiary) operating reserves. Primary reserve covers any variations within a half-hour time horizon. This ensures that there is more than sufficient time for activating (which is done manually in the U.K.) and ramping up the secondary reserve in order to release the primary reserve. Milligan et al. [327] and Holttinen et al. [343] provide overviews of further reserve considerations as applied in North America and Europe.

The main sources of unpredictable variations in demand and generation are load forecast errors, forced power plant and transmission outages and wind forecast deviations. Weber [333] cites Hufendiek [362] and Maupas [363], which quantify the day-ahead load forecast error with 2% for Germany and 1% for France. This is in line with work by Freris and Infield [364], who mention an average error of 1.3% for the UK, with rarely any deviations above 3%. Over the period 2001 – 2010, forced power plant outages in Germany amounted to an average value of 6.0% for fossil fuel-fired and 4.8% for nuclear power plants [365][138]. According to UKERC the chance that an individual plant is not available amounts to 10%, including transmission failures [323][139].

Wind forecast deviations depend on the weather conditions and increase significantly with the forecasting period. In Germany, the root mean square error amounts to 3.1% for intra-day, 4.4% for day-ahead, and 5.8% for forecasts 2 days ahead of time, measured as shares of the total wind capacity [333]. Measured as share of the expected production, the day-ahead forecast error can increase to 20%. This is because of the low load factor of wind power. Over a half an hour and a four hour time horizons, the standard variations of the *change* in wind output in the UK are 1.4% and 9.3% of the installed wind capacity respectively [361]. The standard deviation of the *uncertainty* of wind generation is however lower, with Milborrow [366] citing a value of around 6% over a four hour horizon. For a detailed assessment of wind power variations in Nordic countries refer to Holttinen [358].

The reserve provision of power plants to balance such variations depends on their costs and operational constraints. These include their availability, ramping rates and minimum stable generation levels. The level of detail with regard to modelling such dynamics has to be carefully chosen. It will be important to capture the key implications for energy system investments, but without unnecessarily adding layers of complexity to the model.

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[138] Note that forced outages with 'no scope for scheduling' as defined by VGB Power Tech and Eurelectric refer to outages which can be delayed by less than 12 hours [365]. Only a fraction of these outages will therefore require short-term balancing.

[139] However, an unpredictable variation which draws on the system's operating reserve only occurs during the time immediately after the plant outage occurs.

2.2.2 Implementation in OSeMOSYS

In order to integrate balancing and the related operating reserve requirements into OSeMOSYS, two different time horizons with associated forecast errors are assessed for each modelling region. These are referred to as 'primary reserve' for the shorter time horizon and 'secondary reserve' for the longer one. Given the numerous existing definitions as outlined in Section 1.3 of Part B of this thesis, it is left up to the analyst to decide on the actual timeframes assigned to these reserves[140]. For example, what is defined as secondary and tertiary reserve requirements in some countries may be combined in the model within one reserve class called secondary reserve. Both upward and downward reserve requirements can be modelled. Given the variety of applied approaches to determine the scale of operating reserve requirements, their exogenous definition is left to the analyst. This is intended to ensure the models generic applicability.

Based on ramping characteristics, the maximum upward and downward primary and secondary reserve contributions of each technology have to be entered. Minimum stable generation levels have to be defined for each technology. Some offline plants might be able to ramp up fast enough to provide upward reserve if needed. Theoretically, all upward reserve could be met by such 'quick-start' units. While this might technically be possible, it might not be economic due to start-up costs. A minimum share of the upward reserve can therefore be specified which has to be provided by plants which are online and generate electricity. Further, cycling characteristics can be defined by confining the maximum change of online capacity and generation of a technology from one time slice to another. This enables an indirect consideration of start-up costs. In the model, the term online capacity was introduced to refer to the design capacity of all power plants which form part of the same technology category and are currently generating electricity.

The technology definition in OSeMOSYS is wide and flexible. It comprises any fuel use and conversion, from resource extraction to appliances. Therefore, the provision of operating reserve is not limited to power plants. For example, the use of electric heat-pumps or electric vehicles for short-term balancing could be considered. Naturally, the minimum stable generation level for demand-side

[140] For future applications, OSeMOSYS could be configured to represent additional intermediate classes of reserves.

technologies could be set to zero. They would then be considered as quick-start units which could be brought online whenever needed.

Based on the defined technology characteristics, OSeMOSYS will ensure optimised technology investments over the modelling period. For all time slices, it will decide which plants to operate, both for electricity generation and the provision of reserve services. Refer to Section 3.3 of Part B of this thesis for further information on the implementation in OSeMOSYS.

2.2.3 Limitations

While multi-regional modelling is supported by the code enhancements, the trading of operating reserve between different regions cannot yet be fully considered: upward reserve may be traded as it is modelled as a 'dummy fuel' (refer to Section 3.3 of Part B). Modelling the trading of downward reserve will however require some additional constraints to ensure it can be shared between various modelling regions. Once fully implemented, the facilitated spatial disaggregation may provide valuable insights with regard to the role of transmission for the provision of operating reserve and might help identify bottlenecks.

In the presented model enhancements, several cost implications of balancing requirements are considered. These include investments in flexible generation options and their electricity generation costs. Further, the provision of upward reserve requires an increased operation at part-load. To compensate this, investments in additional system capacities are required, which are considered within OSeMOSYS. Also, an indirect consideration of start-up costs is included.

However, a 'steady-state' is modelled. In this state plants are ready to provide reserve. It does not consider the actual provision of reserve, but rather the implications of having sufficient reserve at hand. Obviously, the actual activation of a reserve would cause a deviation of the electricity generation in this steady-state with associated costs, e.g., to compensate an outage. Further, costs associated with the cycling of a technology were ignored. Cycling is allowed at constant efficiencies in-between their minimum stable generation levels and their maximum outputs.

While there are ways to integrate the varying efficiencies associated with operation at part load and the cost implications of the actual reserve provision, this would add layers of complexity to the model. Due to the associated increases in data and performance requirements, these effects were therefore not considered.

Also, the additional input data required to model varying efficiencies is afflicted with uncertainties about future technology performance. The common modelling time horizon for power plant expansion studies necessarily spans several decades given the long economic lives of power plant investments. It is therefore difficult to forecast if and to what extent, for example, increasing wind penetration levels might result in changes in the design of nuclear power plants. If power plants are designed from the outset to provide reserve services, this might as well go along with higher efficiencies in the lower part of their operating range. Due to the uncertainties involved in estimating such future technology improvements, adding this level of detail in the model might therefore not necessarily improve its accuracy.

3 Conceptual Description and Algebraic Formulation

This section provides detailed mathematical descriptions of the code enhancements. For applications of these enhancements refer to Sections 4 and 5 of Part B of this thesis.

3.1 Key Elements of the Code Expansions

All code enhancements presented in Section 3 refer to OSeMOSYS in its beta version as of 2012.06.01, as downloadable via the OSeMOSYS website (www.osemosys.org). This version is referred to as the core code of the model. Box 3 provides a brief explanation of all indices used in the following algebraic formulations.

Box 3: Indices Used to Enhance Integration Between Timeframes

y	…	Year
l	…	Time slice: i.e., a fraction of the year with specific demand or supply characteristics.
ll	…	Same as time slice; used if independent indices are required .
t	…	Technology: i.e., any system component consuming or generating a fuel.
f	…	Fuel, e.g., electricity or coal.
ff, fff	…	Same as fuel; used if independent indices are required to differentiate electricity from primary and secondary reserve, which are all modelled as fuels.
r	…	Region

All parameters which need to be entered by the analyst for the calculation of the following enhancements are described in Box 4[141]. Parameters are indicated in bold within the algebraic formulations to differentiate them from model variables. As in Section 2.3 of Part A of this thesis and complying with the OSeMOSYS naming convention, rather long parameter and variable names were chosen to increase readability.

Box 4: Parameters Used to Enhance Integration Between Timeframes

$\mathbf{CapacityFactor_{y,t,r}}$ – The ratio of available maximum capacity to the design capacity. Entered as a fraction.

$\mathbf{CapacityToActivityUnit_{t,r}}$ – Relates the unit that capacity is measured in to the unit of production.

$\mathbf{ElectricityForTransmissionTag_{f,r}}$ – Lets the model know the fuel name chosen for electricity generated by power plants. Equals 1 for electricity and 0 for all other fuels.

$\mathbf{MaxOnlineCapacityReduction_{y,t,r}}$ – Maximum reduction of the online capacity of a technology from one time slice to another. Entered as percentages of the online capacity.

$\mathbf{MaxGenerationReduction_{y,t,r}}$ – Maximum generation reduction from one time slice to another. Entered as percentages of the online capacity.

$\mathbf{MaxPrimReserveDown_{y,t,r}}$ – Shares of the available capacity of a technology which may

[141] Refer to Howells et al. [101] for further parameters of the core code.

MaxPrimReserveUp$_{y,t,r}$
MaxSecReserveDown$_{y,t,r}$
MaxSecReserveUp$_{y,t,r}$ contribute to meet a demand for primary or secondary downward or upward reserve. Entered as fractions.

MinStableOperation$_{y,t,r}$ – Minimum share of the online capacity at which a power plant may be operated to generate electricity.

MinPrimReserveUpOnline$_{y,r}$ –
MinSecReserveUpOnline$_{y,r}$ Minimum shares of upward reserve demands which have to be met by plants which are online.

PeakElectricityDemandEntered$_{y,r}$ – Has to be set equal to the model variable PeakElectricityDemandCalculated$_{y,r}$. Has to be entered manually in a second model run to ensure the linearity of the model.

PrimReserveDownCapacityDemand$_{y,l,r}$ –
PrimReserveUpCapacityDemand$_{y,l,r}$ Demand for primary downward and upward reserves, measured in the unit of power, e.g., GW.

ReliabilityConventionalPlants$_{y,r}$ – Reliability of power system without wind. Entered as a fraction.

ReserveMarginTagTechnology$_{y,t,r}$ – Defines each technology's contribution to the overall system's reserve margin. Entered as a fraction.

SecReserveDownCapacityDemand$_{y,l,r}$ –
SecReserveUpCapacityDemand$_{y,l,r}$ Demands for secondary downward and upward reserves, measured in the unit of power, e.g., GW.

SpecifiedDemandProfile$_{y,l,f,r}$ – Indicates the proportion of the yearly energy demand in each time slice. For each year its sum must equal 1.

TimeSliceLinkTag$_{l,ll,r}$ – Links time slices with each other to limit generation and online capacity reductions. Can as well be used to link future to past time slices to limit the capacity reduction in one time slice based on a future online capacity.

WindCapacityCreditSwitch – If equal to one, the wind capacity credit will be calculated using mixed integer programming.

WindDispersionCoefficient$_{y,r}$ – Should equal 0.96 for a single plant and zero for a wind park with no output correlation between individual plants. Realistic values for wind parks are between 0.3 – 0.6.

WindTechnologyTag$_{t,r}$ – Lets the model know the technology name chosen for wind power. Equals 1 for wind power and 0 for all other technologies.

YearSplit$_{y,l}$ – The length of each time slice as a fraction of the year. Entered as fractions. Their sum over a year should equal one.

The following conceptual descriptions employ cross references indicated by bracketed labels. These refer to the algebraic formulations of the OSeMOSYS implementation presented in Section 3 of Part B of this thesis. Further, they help identify the corresponding lines of the final code as presented in Annex D, where they appear at the beginning of each constraint.

3.2 Capacity Credit of Wind Power

3.2.1 Conceptual Description

This section outlines the main principles of the OSeMOSYS implementation of the capacity credit formula as presented by Voorspools and D'haeseleer [51]. These principles are revisited and explained in more detail when presenting the algebraic formulations immediately after this conceptual description.

The capacity credit of wind power is modelled for each modelling region. The formulas (Eq1) and (Eq2) presented in Section 2.1.1 of Part B were implemented as a piece-wise linear approximations separated into six segments. Penetration rates within the first and last segments were assumed to result in a constant wind capacity credit. The error introduced by the linear approximation was found to be negligibly small, especially taking into account the limitations of the capacity credit formula as mentioned in Section 2.1.2 of Part B.

First, some key variables are calculated: The peak electricity demand is derived by summing up the exogenously defined final electricity demand and any electricity consumption of the modelled technologies (WCC1). The wind power penetration is calculated by dividing the total wind power plant capacity by the peak electricity demand (WCC2). This constitutes a division of two variables, which is not supported by a linear programming solver like GLPK, which OSeMOSYS currently draws on. Therefore, the peak electricity demand has to be exogenously defined in a first model run and updated, if required, by the calculated value (WCC1).

While not necessarily required, MATLAB was used to run these iterative model runs and cross-check that the calculated and the entered peak demand equal[142]. Then, the annual, average wind capacity factor is derived from the capacity factors which need to be entered by the analyst for each time slice in a year (WCC3). In the core code of OSeMOSYS, a parameter has to be specified which comprises the capacity credits of all technologies. The initially entered capacity credit of wind is extracted from this parameter in (WCC4).

[142] Note that if no technologies with varying activity levels use electricity as an input fuel, or if any own consumption is implicitly considered by a reduced output, only one model run is required to determine the peak demand. The final results can then be derived from the second model run.

The calculated penetration rate of wind is assigned to one of the six segments of the linear approximation (WCC5 – WCC7). Then, the capacity credit is calculated in (WCC8) based on (Eq1). Mixed integer programming has to be introduced for this purpose. The analyst may however switch all mixed integer programming equations off (and thus also the calculation of the capacity credit) in case no capacity credit calculations are required, or if previous calculations are not expected to change. This may be done to speed up the model runs.

In the core code of OSeMOSYS it is ensured that the total capacity of the contributions of all technologies to the system reserve has to be larger than the peak electricity demand plus a reserve margin (RM1 - RM3 in the core code). This additional margin is required to ensure system adequacy, even if some plants are unavailable. The calculation of the expected contribution of wind power to the system reserve would require a multiplication of two variables, the capacity credit of wind power and its total capacity. Multiplying two variables is not allowed when using linear programming. Therefore, the capacity credit has to be exogenously defined in a first model run and updated, if required, by the calculated value[143]. Again, MATLAB was used to run these iterative model runs and ensure that the calculated capacity credit (WCC8) equals the entered contribution to the reserve margin (WCC4).

The required capacity investments to ensure adequacy are minimised as part of the objective function of OSeMOSYS. Based on these code expansions, the reduced contribution of wind power to the capacity credit as penetration rates increase will therefore be compensated by optimised additional technology investments.

3.2.2 Key Variables

First, the input variables to (Eq1 & Eq2) are calculated (refer to Section 2.1.1 of Part B).

The peak electricity demand is derived from the sum of the rate of final electricity demand and the rate of electricity used by technologies during the peak demand time slice (WCC1). Equation (WCC1) is only calculated when several conditions apply. First, it is only calculated for the peak demand time

[143] As long as wind penetration rates don't change, no further iteration is required if a constant dispersion coefficient and a constant conventional power plant reliability are assumed.

slice. The peak demand time slice is identified by calculating the maximum demand per time span, i.e., the maximum value of the division of the demand share in a time slice by its duration. Further, it is only applied for the fuel electricity. The ElectricityForTransmissionTag lets the model know the name of this fuel, as chosen by the analyst. It equals one for the fuel produced by power plants and zero for all other fuels[144]. Similarly, the WindTechnologyTag lets the model know the technology name chosen for wind power. The condition in (WCC1) that this tag has to equal one ensures through the CapacityTo-ActivityUnit that the peak demand is calculated in the capacity units assigned to wind power[145].

$$\forall_{y,l,t,f,r}: \max(\boldsymbol{SpecifiedDemandProfile_{y,l,f,r}/YearSplit_{y,l}})\ \&\ \boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1\ \&\ \boldsymbol{WindTechnologyTag_{t,r}} = 1: (RateOfDemand_{y,l,f,r} + RateOfUse_{y,l,f,r})/\boldsymbol{CapacityToActivityUnit_{t,r}} = PeakElectricityDemandCalculated_{y,r} \qquad \text{(WCC1)}$$

The wind power penetration is calculated by dividing the total wind power plant capacity by the peak electricity demand entered by the analyst (WCC2). The peak electricity demand calculated in (WCC1) should obviously have the same value as the peak electricity demand entered in (WCC2). However, it cannot directly be used as an input value for equation (WCC2). This would result in a division of two variables, and therefore a non-linear problem formulation. It therefore has to be cross-checked externally that the calculated peak demand equals the entered demand.

$$\forall_{y,t,r}: \boldsymbol{WindTechnologyTag_{t,r}} = 1: TotalCapacityAnnual_{y,t,r}/\boldsymbol{PeakElectricityDemandEntered_{y,r}} = WindPenetration_{y,r} \qquad \text{(WCC2)}$$

The average capacity factor of wind power is calculated by multiplying its entered capacity factors for each time slice with their duration share within a year. These multiplications are summed up for each year.

$$\forall_{y,t,r}: \boldsymbol{WindTechnologyTag_{t,r}} = 1: \textstyle\sum_l \boldsymbol{CapacityFactor_{y,t,l,r}} * \boldsymbol{YearSplit_{y,l}} = WindAverageCapacityFactor_{y,r} \qquad \text{(WCC3)}$$

144 Several fuel types and names may be defined to represent electricity at different levels within the energy system, e.g., at transmission, distribution or end-use level.

145 The units used for wind may differ from those for, e.g., a coal mine. Refer to footnote 110 for further explanations regarding the CapacityToActivityUnit.

The capacity credit for all technologies is entered within the parameter ReserveMarginTagTechnology. This parameter of the core code of OSeMOSYS defines each technology's contribution to the system's reserve margin. Its value should equal to one for power plants which are fully available to meet peak demand (assuming no outage occurs). Note that the reserve margin is unrelated to the operating reserve as presented in Section 3.3 of Part B of this thesis. It is simply a reliability indicator and calculated as the total capacity contribution towards the reserve margin divided by the peak demand. The initially entered capacity credit of wind is extracted from the ReserveMarginTagTechnology parameter in (WCC4).

$$\forall_{y,t,r}: \boldsymbol{WindTechnologyTag_{t,r}} = 1:$$
$$\boldsymbol{ReserveMarginTagTechnology_{y,t,r}} = WindCapacityCreditEntered_{y,r} \quad \text{(WCC4)}$$

3.2.3 Capacity Credit Formula

The capacity credit formulas (Eq1) and (Eq2) were implemented as piece-wise linear functions separated into 6 segments based on the following wind penetration levels: 0% - 1%, 1% - 5%, 5% - 10%, 10% - 20%, 20% - 35%, and > 35%. The implementation of piecewise linear functions in GLPK has been modelled following the conceptual description provided by Morrison and Makhorin [367].

First, a tag is assigned to each segment. This tag is defined to be either one or zero. Thus, mixed integer programming is applied. A value of one is assigned if the penetration rate falls within a specific segment, and zero otherwise. Therefore, for every year and region, only one of the tags may be equal to one (WCC5).

The parameter WindCapacityCreditSwitch was introduced to allow the analyst to switch all mixed integer programming equations (and thus the calculation of the capacity credit) on or off. (WCC5) and the following equations will only be calculated if its value equals one. This was done to speed up the model runs in case no capacity credit calculations are required, or if previous calculations are not expected to change.

$$\forall_{y,r}: \boldsymbol{WindCapacityCreditSwitch} = 1:$$
$$Segment1Tag_{y,r} + Segment2Tag_{y,r} + Segment3Tag_{y,r} + Segment4Tag_{y,r} +$$
$$Segment5Tag_{y,r} + Segment6Tag_{y,r} = 1 \quad \text{(WCC5)}$$

The segment fraction which represents the wind power penetration rate within a segment is defined to be smaller or equal than the tag of the segment (refer to WCC6a for segment 1)[146]. For example, for a penetration rate of 7.5%, the fraction value would be 50% for the third segment (5% - 10%) and zero for all others.

$$\forall_{y,r}: \boldsymbol{WindCapacityCreditSwitch} = 1:$$
$$Segment1Fraction_{y,r} \leq Segment1Tag_{y,r} \quad \text{(WCC6a)}$$

Therefore, the actual penetration can be calculated by multiplying this segment fraction with the width of the segment in per cent, and adding the penetration rate at the beginning of the segment. For example, for a penetration rate of 7.5% this would result in 50% x (10% - 5%) + 5% = 7.5%. This logic is applied to all segments. The penetration rate at the beginning of a segment is multiplied by the segment tag to ensure that only the penetration rate of one segment is added in (WCC7).

$$\forall_{y,r}: \boldsymbol{WindCapacityCreditSwitch} = 1: (Segment1Fraction_{y,r} * 1 + Segment2Tag_{y,r} * 1 + Segment2Fraction_{y,r} * 4 + Segment3Tag_{y,r} * 5 + Segment3Fraction_{y,r} * 5 + Segment4Tag_{y,r} * 10 + Segment4Fraction_{y,r} * 10 + Segment5Tag_{y,r} * 20 + Segment5Fraction_{y,r} * 15 + Segment6Tag_{y,r} * 35 + Segment6Fraction_{y,r} * 965)/100 = WindPenetration_{y,r} \quad \text{(WCC7)}$$

Equations (WCC5 – WCC7) are required to calculate which segment contains the penetration rate and which fraction of the segment represents this rate. The capacity credit calculation in (Eq1) was translated into ($WCC8_{initial,a}$) when applying OSeMOSYS' naming conventions. It is used to calculate the capacity credit at the end of each segment.

$$\forall_{y,r}: \boldsymbol{WindCapacityCreditSwitch} = 1 \ \& \ \boldsymbol{WindPenetration_{y,r}} = 1\%, 5\%, 10\%, 20\% \ or \ 35\%:$$
$$WindCapacityCreditCalculated_{y,r} = 32.8/(0.306 + \boldsymbol{WindDispersionCoefficient_{y,r}}) * WindAverageCapacityFactor_{y,r}/\boldsymbol{ReliabilityConventionalPlants_{y,r}} * (1 + 3.26 * \boldsymbol{WindDispersionCoefficient_{y,r}} * e^{-0.1077(0.306+\boldsymbol{WindDispersionCoefficient_{y,r}})*(WindPenetration_{y,r}-1)}) \quad (\text{WCC8}_{\text{initial,a}})$$

[146] The same logic applies for all other segments. The corresponding formulas are referred to as (WCC6a) – (WCC6f) in the actual code implementation.

In line with (Eq2), its value for a penetration rate of one per cent applies for the whole first segment from 0% - 1%. Further, its value for a rate of 35% is applied for the whole sixth segment. This was done due to the small changes in the calculated wind capacity credit for higher penetration levels. Similarly to (WCC7), all other linearly approximated values were calculated as the difference of the capacity credit at the end of two subsequent segments, multiplied with the segment fraction representing the penetration rate. Further, the capacity credit at the end of the segment preceding the one containing the penetration rate is added.

$$\begin{aligned}
&\forall_{y,r}: \boldsymbol{WindCapacityCreditSwitch} = 1:\\
&(Segment1Tag_{y,r} + Segment2Tag_{y,r}) * CapacityCreditEndOfSegment1_{y,r} +\\
&Segment2Fraction_{y,r} *\\
&\left(CapacityCreditEndOfSegment2_{y,r} - CapacityCreditEndOfSegment1_{y,r}\right)\\
&+ Segment3Tag_{y,r} * CapacityCreditEndOfSegment2_{y,r} + \ Segment3Fraction_{y,r} *\\
&* \left(CapacityCreditEndOfSegment3_{y,r} - CapacityCreditEndOfSegment2_{y,r}\right)\\
&+ Segment4Tag_{y,r} * CapacityCreditEndOfSegment3_{y,r} + Segment4Fraction_{y,r} *\\
&* \left(CapacityCreditEndOfSegment4_{y,r} - CapacityCreditEndOfSegment3_{y,r}\right)\\
&+ Segment5Tag_{y,r} * CapacityCreditEndOfSegment4_{y,r} + Segment5Fraction_{y,r} *\\
&* \left(CapacityCreditEndOfSegment5_{y,r} - CapacityCreditEndOfSegment4_{y,r}\right)\\
&+ Segment6Tag_{y,r} * CapacityCreditEndOfSegment6_{y,r}\\
&= WindCapacityCreditCalculated_{y,r} \qquad (\mathrm{WCC8}_{\mathrm{initial,b}})
\end{aligned}$$

A multiplication of variables is not allowed in OSeMOSYS, as the solver GLPK cannot solve non-linear equation systems. However, in ($\mathrm{WCC8}_{\mathrm{initial,a}}$) the average capacity factor is multiplied with *e* to the power of the wind penetration, and in ($\mathrm{WCC8}_{\mathrm{initial,b}}$) the capacity credit at the end of a segment is multiplied with the segment fraction. All of those variables can directly be calculated from the parameters entered by the analyst. Therefore, in the implementation of the OSeMOSYS code, equations (WCC3), ($\mathrm{WCC8}_{\mathrm{initial,a}}$) and ($\mathrm{WCC8}_{\mathrm{initial,b}}$) are combined in one single bulky equation (WCC8). (WCC3) is however maintained in the code for reporting purposes.

In the core code of OSeMOSYS, the contribution of a technology to the reserve margin is determined by multiplying the ReserveMarginTagTechnology with the calculated total capacity of a technology. The ReserveMarginTagTechnology parameter represents the capacity credits of the available technologies. While the capacity credit is calculated in (WCC8), it cannot be directly integrated into the ReserveMarginTagTechnology, as a multiplication of two variables is not allowed. Therefore, a first model run is required to calculate the capacity credit of wind, which then has to be entered manually in the ReserveMarginTagTechnology in a second model run[147], i.e., (WCC4) has to equal (WCC8).

3.3 Balancing

3.3.1 Conceptual Description

This section outlines the main principles of the code additions and provides a 'higher-level guide' to the algebraic formulation. The same principles are revisited and explained in more detail when presenting the algebraic formulations immediately after this conceptual description.

Throughout every year, all technologies have to provide at least the amount of reserves as specified by the analyst (R1 – R4). The upward reserve demands are represented in OSeMOSYS as a 'dummy' fuel. The minimum available capacity of a technology within OSeMOSYS is determined by the maximum sum of the electricity generation and reserve provision in all modes of operation within a year. This ensures the availability of sufficient capacities on top of those required for electricity generation in order to be able to provide upward reserve. Downward reserves are implemented as constraints on the minimum electricity generation requirements.

Within OSeMOSYS, a technology is assumed to comprise an indefinite number of power plants[148]. The online capacity of the power plants associated with a technology has to be smaller or equal than the total available capacity of this technology (R5). Based on ramping characteristics, maximum shares of the online capacity can be defined which a technology can contribute to meeting downward reserves (R6 & R7). The provision of upward reserve may not be dependent on the online capacities. Some technologies might be able to start up fast enough to provide upward reserve without the need for any plants to be online. A differentiation based on ramping rates and minimum stable generation levels is required.

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147 As long as wind penetration rates don't change, no further iteration is required if a constant dispersion coefficient and a constant conventional power plant reliability are assumed.

148 In order to avoid mixed-integer programming, no concrete power plant block sizes are considered when modelling reserve requirements. OSeMOSYS can decide freely how to split those up in online and offline power plants.

First, technologies are assessed whose entered maximum capacity contribution to primary and secondary reserve is larger or equal than their minimum stable operation level. For example, ramping rates could allow a technology to bring 120 MW online within the specified reserve timeframe. If its minimum operation is at 100 MW, it is therefore assumed to be able to ramp up from zero output above its operating level (or back down to zero output) fast enough to contribute fully to meeting reserve demands[149]. In this case, the upward reserve provided is constrained by the total available capacity times the maximum possible reserve contribution of a technology (R8 & $R9_{initial}$). It can provide as much downward reserve as it is generating electricity ($R10_{initial}$). Its online capacity has to be at least as large as the capacity required for electricity generation (R11). Further, keeping capacity online requires an electricity generation at or above the minimum stable generation level ($R12_{initial}$). This ensures as well that there is a cost associated with keeping capacity online.

Second, technologies are investigated whose maximum contribution to primary and secondary reserve is smaller than the minimum stable operation level. The minimum operation level could for example be 100 MW and the reserve contribution only 20 MW. Such technologies can therefore not be ramped down to zero output or back up to their operating level within the reserve timeframe. They have to operate at some point above their minimum stable operation level and in-between their operating range in order to provide reserve services.

The difference between the electricity generation and the minimum stable operation level limits the maximum downward reserve which the online plants can provide. Similarly, the difference between the potential maximum generation of a plant and its electricity generation limits the maximum upward reserve of these plants.

The upward reserve provided is now constrained by the ramping characteristics of the online capacity[150] ($R13_{initial}$ & R14). The minimum electricity generation can be calculated be adding the provided primary and secondary downward reserve to the minimum stable generation of the online capacity (continuous arrows in Fig. 13) (R15). Further, it has to be ensured that at least as much capacity is online as the provided power output plus all provided upward reserve services (dashed arrows in Fig. 13) (R16).

149 This might be unrealistic for a very short time horizon for primary reserve. However, it is up to the analyst to decide which time horizon to associate with primary and secondary reserve.

150 The maximum downward reserve is derived from the online capacity in (R6 & R7).

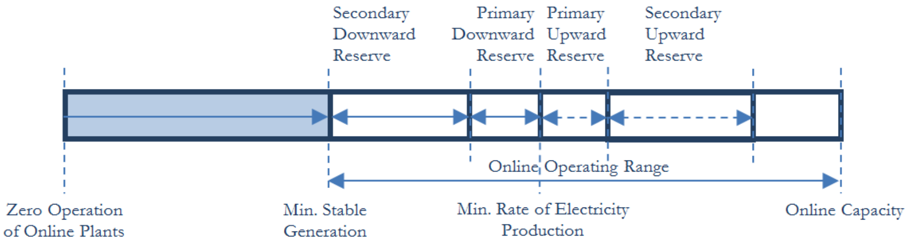

Fig. 13: Calculation of minimum electricity production and online capacity in (R15 & R16)

Finally, technologies are assessed whose maximum contribution to primary reserve is smaller than the minimum stable operation level, while the contribution to secondary reserve is larger. In this case all secondary reserve can be met by ramping up from zero output to above the minimum operating level (or down back to zero output). The provision of primary reserve however requires an operation below the online capacity in order to be able to ramp up the generation if needed (R17). The primary upward reserve provided is again constrained by the ramping characteristics of the online capacities (R13)[151].

Secondary upward reserve can be provided by offline plants and is therefore independent of the online capacity. It only has to be constrained based on the ramping characteristics of the total available capacity of a technology (R9). The required minimum electricity generation has to be at least as high as the secondary downward reserve provided. Any additional primary downward reserve requires an operation above the minimum stable generation level (R18 & R10). All online plants forming part of a technology have to generate electricity at or above their minimum stable generation level (R12).

The analyst is given the option to enter a minimum share of upward reserve which has to be provided by online plants (R19 & R20). The calculations of the upward reserves from online plants are differentiated based on ramping characteristics in (R21 – R27). It might not be desirable or realistic to allow the model to freely vary the online capacity of a technology from one time slice to another. Therefore, the analyst can define a maximum reduction of the online capacity from one time slice to another (R28). This enables an indirect consideration of start-up costs. It might as well be desirable to constrain the

151 The maximum downward reserve is derived from the online capacity in (R6 & R7)

electricity output based on ramping characteristics, especially if time slices represent a rather short period of time within a specific day-type. Therefore, the analyst can as well define a maximum reduction of the generation from one time slice to another (R29).

3.3.2 Meeting Reserve Demands

Equations (R1 – R4) ensure that within every year and time slice, all technologies provide at least the amount of primary and secondary reserve that has been specified by the analyst. The CapacityToActivityUnit is required to ensure that the same units are used on both sides of the inequality.

The upward reserve demands are modelled as a 'dummy' fuel named "PrimReserveUp" and "SecReserveUp"[152] (R1 & R2). In the core code of OSeMOSYS, each technology may consume and produce different fuels in different modes of operation [101]. When modelling reserve, the analyst has to ensure that electricity is generated in one mode of operation while the dummy reserve fuels are provided in two other modes of generation.

The total capacity of a technology within OSeMOSYS is determined by the maximum sum of the electricity generation and reserve provision in all modes of operation within a year. This ensures the availability of sufficient capacities on top of those required for electricity generation in order to be able to provide upward reserve. Note that no input fuel should be defined for the modes of operation associated with the provision of reserve. This is because the provision of reserve is not assumed to consume any input fuels (as opposed to the actual activation of a reserve).

$$\forall_{y,l,f=PrimReserveUp,r}: \sum_t RateOfProductionByTechnology_{y,l,t,f,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq \boldsymbol{PrimReserveUpCapacityDemand_{y,l,r}} \quad \text{(R1)}$$

$$\forall_{y,l,f=SecReserveUp,r}: \sum_t RateOfProductionByTechnology_{y,l,t,f,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq \boldsymbol{SecReserveUpCapacityDemand_{y,l,r}} \quad \text{(R2)}$$

[152] This is a convenient deviation from the normal naming convention of OSeMOSYS, which gives the analyst the freedom to choose any names. Given that only fuel demands for these two specific reserve fuel types can be modelled, this simplification does not comprise the model's overall flexibility.

In the core code of OSeMOSYS, the rate of activity is a driving key variable, e.g., for the calculation of the capacity of a technology. The fuel production of a technology is calculated by multiplying the 'rate of activity' with the output activity ratio. Using the rate of production in equations (R1 & R2) requires the output activity ratios to be set equal to one. The rate of production will therefore equal the rate of activity of a technology. Accordingly, the efficiencies for electricity generation have to be defined by using input activity ratios larger than one (i.e., by entering heat rates or the reciprocal of the efficiencies). While this is the standard approach for modelling power plants in OSeMOSYS, it is strictly speaking not a requirement. Refer to Howells et al. [101] for more information about the definition and use of the rate of activity and input and output activity ratios.

Similarly as in (R1 & R2), the total contribution of all technologies to downward reserve has to be equal or larger than the downward reserve requirements (R3 & R4).

$$\forall_{y,l,r}: \sum_t PrimReserveDownByTechnology_{y,l,t,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq \boldsymbol{PrimReserveDownCapacityDemand_{y,l,r}} \tag{R3}$$

$$\forall_{y,l,r}: \sum_t SecReserveDownByTechnology_{y,l,t,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq \boldsymbol{SecReserveDownCapacityDemand_{y,l,r}} \tag{R4}$$

3.3.3 <u>Considering Ramping Characteristics</u>

If power plants are used to provide operating reserves, this may have implications for their minimum electricity generation requirements. For example, a share of the upward reserve requirements may have to be provided by power plants which are online and operate at least at their minimum stable generation level. Further, plants may need to operate above their minimum stable generation in order to be able to provide downward reserve. Different minimum electricity generation requirements apply depending on the ramping rates and minimum stable operation levels of the individual technologies.

In order to avoid mixed-integer programming, no concrete power plant block sizes are used when calculating reserve requirements. For example, one technology may represent 8000 MW of thermal power plants with a minimum stable operation at 45% of its capacity. It is then assumed that this technology represents an indefinite number of power plants. As such, it is able to generate, e.g., at 2000 MW. This could be interpreted as plants with 2000 MW capacity being online and generating at their maximum output, while plants with a combined capacity of 6000 MW are currently shut down. This notion of separating a technology in online and offline plants is maintained in the following formulations.

The following inequalities all serve to constrain the online capacities, the provision of reserve, and electricity generation requirements for each technology.

The online capacity of a technology has to be smaller or equal than the total available capacity. The available capacity in each time slice is calculated as the total capacity that is available within a year, de-rated by the capacity factor (R5).

$$\forall_{y,l,t,r}: \quad OnlineCapacity_{y,l,t,r} \leq \boldsymbol{TotalCapacityAnnual_{y,t,r}} * \boldsymbol{CapacityFactor_{y,t,l,r}} \tag{R5}$$

3.3.3.1 Contributing to Downward Reserve up to the Technical Maximum

The analyst can define maximum shares of the online capacity which a technology can contribute to meet primary or secondary downward reserves. These shares are multiplied with the online capacity to limit the provision of downward reserve of each technology (R6 & R7).

$$\forall_{y,l,t,r}: PrimReserveDownByTechnology_{y,l,t,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxPrimReserveDown_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \tag{R6}$$

$$\forall_{y,l,t,r}: SecReserveDownByTechnology_{y,l,t,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxSecReserveDown_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \tag{R7}$$

Similarly, the analyst can define maximum shares for the upward reserve contribution. However, the provision of upward reserve might not be dependent on the online capacities. Some technologies might be able to start up fast enough to provide upward reserve without the need for any plants to be online. A differentiation based on ramping rates and minimum stable generation levels is required.

3.3.3.2 Ramping Down to and Back up from Zero Output

If both the maximum contribution to primary and secondary reserve is larger or equal than the minimum stable operation, a plant can be ramped down to zero output or back up to its operating level fast enough to meet all downward and upward reserve demands[153].

The upward reserve provided is only constrained by the total available capacity times the maximum possible reserve contribution of a technology. The available capacity in each time slice is calculated as the total capacity that is available within a year, de-rated by the capacity factor (R8 & R9$_{\text{initial}}$).

$$\forall_{y,l,t,f=PrimReserveUp,r}: (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \,\&\, \boldsymbol{MaxPrimReserveUp_{y,t,r}} \,\&\, \boldsymbol{MaxSecReserveDown_{y,t,r}} \,\&\, \boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$RateOfProductionByTechnology_{y,l,t,f,r} \leq TotalCapacityAnnual_{y,t,r} * \boldsymbol{CapacityFactor_{y,t,l,r}} * \boldsymbol{MaxPrimReserveUp_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \tag{R8}$$

$$\forall_{y,l,t,f=SecReserveUp,r}: (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \,\&\, \boldsymbol{MaxPrimReserveUp_{y,t,r}} \,\&\, \boldsymbol{MaxSecReserveDown_{y,t,r}} \,\&\, \boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$RateOfProductionByTechnology_{y,l,t,f,r} \leq TotalCapacityAnnual_{y,t,r} * \boldsymbol{CapacityFactor_{y,t,l,r}} * \boldsymbol{MaxSecReserveUp_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \tag{R9$_{\text{initial}}$}$$

A technology which falls into this category can provide as much primary and secondary downward reserve as it is generating electricity. As the name for the fuel ‘electricity’ can be freely chosen, a tag is required to let the model know this name. This is done by setting the tag equal to one for the fuel name associated with the electricity generated by power plants for transmission (R10$_{\text{initial}}$).

[153] This might be unrealistic for a very short time horizon for primary reserve. However, it is up to the analyst to decide which time horizon to associate with primary and secondary reserve.

$$\forall_{y,l,t,f,r}: \boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1 \;\&\; (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \;\&\; \boldsymbol{MaxPrimReserveUp_{y,t,r}} \;\&\; \boldsymbol{MaxSecReserveDown_{y,t,r}} \;\&\; \boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$PrimReserveDownByTechnology_{y,l,t,r} + SecReserveDownByTechnology_{y,l,t,r} \leq RateOfProductionByTechnology_{y,l,t,f,r} \qquad \text{(R10}_{\text{initial}}\text{)}$$

The technology can be ramped up quickly enough from zero output to meet all upward reserve demands. It is therefore not required that more capacity is online than what is needed for electricity generation (R11).

$$\forall_{y,l,t,f,r}: \boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1 \;\&\; (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \;\&\; \boldsymbol{MaxPrimReserveUp_{y,t,r}} \;\&\; \boldsymbol{MaxSecReserveDown_{y,t,r}} \;\&\; \boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$RateOfProductionByTechnology_{y,l,t,f,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{CapacityToActivityUnit_{t,r}} \qquad \text{(R11)}$$

The online plants of such a technology have to generate electricity at or above their minimum stable generation level (R12$_{\text{initial}}$).

$$\forall_{y,l,t,f,r}: \boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1 \;\&\; (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \;\&\; \boldsymbol{MaxPrimReserveUp_{y,t,r}} \;\&\; \boldsymbol{MaxSecReserveDown_{y,t,r}} \;\&\; \boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$OnlineCapacity_{y,l,t,r} * \boldsymbol{MinStableOperation_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \leq RateOfProductionByTechnology_{y,l,t,f,r} \qquad \text{(R12}_{\text{initial}}\text{)}$$

3.3.3.3 Operating Above the Minimum Stable Generation

If both the maximum contribution to primary and secondary reserve is smaller than the minimum stable operation, the plant cannot be ramped down to zero output and back up to its operating level any longer. It therefore has to be generating at some point above the minimum stable operation level and in-between its operating range in order to provide reserve services. The difference between the electricity generation and the minimum stable operation level limits the maximum downward reserve which the online plants can provide. Similarly, the difference between the potential maximum generation of a plant and its electricity generation limits the maximum upward reserve of these plants.

Unlike in the previous case with high ramping rates, the upward reserve provided is now constrained by the online capacity[154] (R13 initial & R14).

$\forall_{y,l,t,f=PrimReserveUp,r}$:
$(\boldsymbol{MaxPrimReserveDown_{y,t,r}}\ or\ \boldsymbol{MaxPrimReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}}\ \&$
$(\boldsymbol{MaxSecReserveDown_{y,t,r}}\ or\ \boldsymbol{MaxSecReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}}$:

$$RateOfProductionByTechnology_{y,l,t,f,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxPrimReserveUp_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \qquad (R13_{initial})$$

$\forall_{y,l,t,f=SecReserveUp,r}$:
$(\boldsymbol{MaxPrimReserveDown_{y,t,r}}\ or\ \boldsymbol{MaxPrimReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}}\ \&$
$(\boldsymbol{MaxSecReserveDown_{y,t,r}}\ or\ \boldsymbol{MaxSecReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}}$:

$$RateOfProductionByTechnology_{y,l,t,f,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxSecReserveUp_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \qquad (R14)$$

The minimum electricity generation can be calculated be adding the provided primary and secondary downward reserve to its minimum stable generation (continuous arrows in Fig. 14). The minimum stable generation is obtained by multiplying the online capacity of a technology by its minimum stable operation level in per cent (R15).

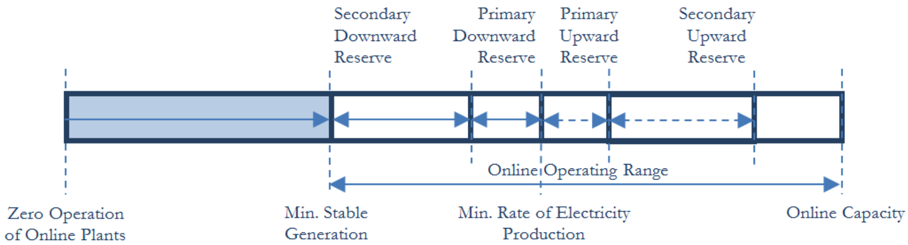

Fig. 14: Calculation of minimum electricity production and online capacity in (R15 & R16)

154 The maximum downward reserve which can be provided has already been considered in (R6 & R7)

$\forall_{y,l,t,f,r}$: $\boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1$ &
$(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ or $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) <$
$\boldsymbol{MinStableOperation_{y,t,r}}$ &
$(\boldsymbol{MaxSecReserveDown_{y,t,r}}$ or $\boldsymbol{MaxSecReserveUp_{y,t,r}}) <$
$\boldsymbol{MinStableOperation_{y,t,r}}$:

$$OnlineCapacity_{y,l,t,r} * \boldsymbol{MinStableOperation_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} + PrimReserveDownByTechnology_{y,l,t,r} + SecReserveDownByTechnology_{y,l,t,r} \leq RateOfProductionByTechnology_{y,l,t,f,r} \quad \text{(R15)}$$

Further, it has to be ensured that at least as much capacity is online as the provided power output plus all provided upward reserve services (dashed arrows in Fig. 14) (R16).

$\forall_{y,l,t,f,ff=PrimReserveUp,fff=SecReserveUp,r}$:
$\boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1$:
$(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ or $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) <$
$\boldsymbol{MinStableOperation_{y,t,r}}$ &
$(\boldsymbol{MaxSecReserveDown_{y,t,r}}$ or $\boldsymbol{MaxSecReserveUp_{y,t,r}}) <$
$\boldsymbol{MinStableOperation_{y,t,r}}$:

$$RateOfProductionByTechnology_{y,l,t,f,r} + RateOfProductionByTechnology_{y,l,t,ff,r} + RateOfProductionByTechnology_{y,l,t,fff,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{CapacityToActivityUnit_{t,r}} \quad \text{(R16)}$$

3.3.3.4 Ramping Down to and Back up from Zero Output for Secondary & Operating Above the Minimum Stable Generation for Primary Reserve

If the maximum contribution to primary reserve is smaller and to secondary reserve larger than the minimum stable operation, only the provision of primary reserve requires an operation above the minimum stable operation. All secondary downward reserve can be met by ramping down to zero output. Similarly, all secondary upward reserve can be met by ramping up from zero output to above the minimum operating level. Given these characteristics, it may be assumed that there are some dedicated plants which provide all the primary reserve by a specific technology. Other plants which form part of the same technology provide all the secondary reserve.

The upward primary reserve provided cannot be larger than the online capacity times the maximum possible reserve contribution of a technology. The validity of ($R13_{initial}$) is therefore extended to cover these cases as well. This is done by removing the restriction that it only applies if the maximum contribution to secondary reserve is smaller than the minimum stable operation.

As opposed to the primary reserve, the upward secondary reserve provided is not dependent on the online capacity. It only has to be smaller than the available capacity times the maximum possible reserve contribution of a technology. The validity of ($R9_{initial}$) is therefore extended to cover these cases as well. This is done by removing the restriction that it is only valid if the primary reserve is larger than the minimum stable operation. The modified equations are referred to as (R9 & R13) in the code implementation.

Those plants which provide the primary reserve have to operate, i.e., generate electricity, below their online capacity if they should be able to ramp up their generation. The plants providing secondary reserve do not require any capacity to be online in order to provide secondary upward reserve. Therefore, only the primary reserve provision needs to be considered when calculating the minimum online capacity in inequality (R17).

$\forall_{y,l,t,f,ff=PrimReserveUp,r}$: $\boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1$ & $(\boldsymbol{MaxPrimReserveDown_{y,t,r}}\ or\ \boldsymbol{MaxPrimReserveUp_{y,t,r}}) <$ $\boldsymbol{MinStableOperation_{y,t,r}}$ & $\left(\boldsymbol{MaxSecReserveDown_{y,t,r}}\ \&\ \boldsymbol{MaxSecReserveUp_{y,t,r}}\right) \geq$ $\boldsymbol{MinStableOperation_{y,t,r}}$:

$$RateOfProductionByTechnology_{y,l,t,f,r} + RateOfProductionByTechnology_{y,l,t,ff,r} \leq OnlineCapacity_{y,l,t,r} * \boldsymbol{CapacityToActivityUnit_{t,r}} \quad \text{(R17)}$$

Those plants which are assumed to provide only primary reserve have to generate electricity at least at their minimum stable generation in order to be able to ramp up if required. In case they also provide primary downward reserve, they have to generate additional electricity allowing them to ramp down to their minimum stable generation level if required. Those plants providing secondary reserve only have to generate electricity in case they are required to provide downward reserve.

The minimum electricity generation for the provision of primary downward reserve can be calculated by assuming that all online plants are contributing to the primary downward reserve up to their technical maximum. In this case it can be calculated how much larger the minimum electricity generation of each technology has to be than its maximum contribution to the primary downward reserve. This is done by dividing the sum of the minimum stable operation and the maximum contribution to primary downward reserve ('a' in Fig. 15) by the latter ('b' in Fig. 15). The actual primary downward reserve provided is therefore multiplied by this factor to calculate the minimum electricity production for meeting primary downward reserve requirements (R18). If secondary reserve is provided as well, it simply needs to be added ('c' in Fig. 15) to calculate the minimum electricity production.

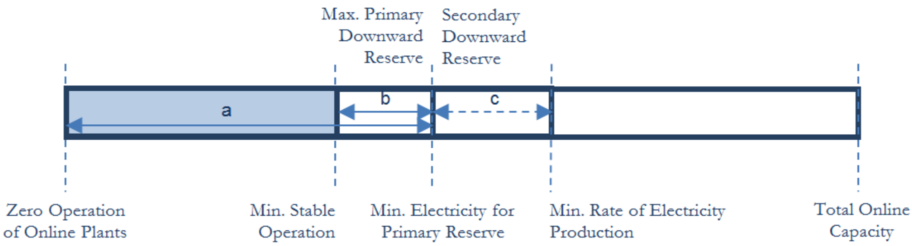

Fig. 15: Calculation of minimum electricity production in (R18)

$$\forall_{y,l,t,f,r}: ElectricityForTransmissionTag_{f,r} = 1 \ \& \ (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \text{ or } \boldsymbol{MaxPrimReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}} \ \& \ (\boldsymbol{MaxSecReserveDown_{y,t,r}} \ \& \ \boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}} \ \& \ \boldsymbol{MaxPrimReserveDown_{y,t,r}} > 0:$$

$$PrimReserveDownByTechnology_{y,l,t,r} * \frac{\boldsymbol{MinStableOperation_{y,t,r}} + \boldsymbol{MaxPrimReserveDown_{y,t,r}}}{\boldsymbol{MaxPrimReserveDown_{y,t,r}}} + SecReserveDownByTechnology_{y,l,t,r} \leq RateOfProductionByTechnology_{y,l,t,f,r} \quad \text{(R18)}$$

In order to avoid a division by zero, (R18) does not cover cases where a technology is not capable of contributing to primary reserve. In this case, the technology would only be required to provide a power output equal to its secondary downward reserve provision. This is because the technology can be ramped down to zero output and back up to its operating level fast enough to meet all downward reserve demands. Inequality ($R10_{initial}$) is extended to cover this case as well. This is done by removing the restriction that it only applies if the maximum contribution to primary reserve is larger or equal than the minimum stable operation. This modified equation is referred to as (R10) in the code implementation. In case a technology also provides primary downward reserve, (R18) will always enforce a higher electricity generation than (R10).

Further, all online plants forming part of one technology have to generate electricity at or above their minimum stable generation level. Similarly to

($R10_{initial}$), ($R12_{initial}$) is extended to cover this case as well and referred to as (R12) in the code implementation.

3.3.4 Operational Constraints

3.3.4.1 Minimum Online Upward Reserve

The previous constraints ensure sufficient electricity generation for the provision of reserve, based on ramping characteristics and minimum stable generation levels. However, potentially all upward reserve requirements could be met by technologies which do not produce any electricity. This could be the case if these technologies are able to ramp up fast enough if needed. The model might prefer such offline technologies as keeping them online requires an operation above the minimum stable generation level with associated generation costs (R12 & R15).

While a provision of reserve by offline technologies might technically be possible, it might not be realistic. Given the energy required to start-up a power plant from a cooled down state, it might be preferable to ensure at least some of the upward reserve is provided by online plants. This might entail that they generate electricity at a potentially higher cost than other technologies, but these costs might be outweighed by the avoided start-up costs. The accurate modelling of the number of start-ups and the associated costs is considered outside of the scope of this energy model. This is due to its coarse temporal resolution and the medium- to long-term timeframe it covers.

Alternatively, the analyst is given the option to enter a minimum share of upward reserve which has to be provided by online plants. These online plants are required to generate electricity at least at their minimum stable operation level. This option is especially important for secondary reserve. Technologies providing primary reserve will most likely have to operate above their minimum stable generation anyway, given their ramping characteristics (as enforced through R10 & R13). However, all of the following constraints are set up for both, primary and secondary reserve. This ensures the model's flexibility with regard to the technology choices and timeframes associated with the two reserve types. These can be freely chosen by the analyst.

The reserve provided by online technologies has to be larger than the demand for upward reserve times the minimum share of this demand which has to be met by online technologies (R19 & R20).

$$\forall_{y,l,r}: \boldsymbol{PrimReserveUpCapacityDemand_{y,l,r}} * \boldsymbol{MinPrimReserveUpOnline_{y,r}} \leq \sum_t PrimReserveUpOnline_{y,l,t,r} \quad \text{(R19)}$$

$$\forall_{y,l,r}: \boldsymbol{SecReserveUpCapacityDemand_{y,l,r}} * \boldsymbol{MinSecReserveUpOnline_{y,r}} \leq \sum_t SecReserveUpOnline_{y,l,t,r} \quad \text{(R20)}$$

In case a technology cannot be ramped up fast enough from zero output, all reserve will have to be provided by online plants. Therefore, in this case the upward reserve provided by online plants equals the production of the fuel 'reserve' (R21 & R22).

$$\forall_{y,l,t,f=PrimReserveUp,r}: (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \text{ or } \boldsymbol{MaxPrimReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$RateOfProductionByTechnology_{y,l,t,f,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} = PrimReserveUpOnline_{y,l,t,r} \quad \text{(R21)}$$

$$\forall_{y,l,t,f=SecReserveUp,r}: (\boldsymbol{MaxSecReserveDown_{y,t,r}} \text{ or } \boldsymbol{MaxSecReserveUp_{y,t,r}}) < \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$RateOfProductionByTechnology_{y,l,t,f,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} = SecReserveUpOnline_{y,l,t,r} \quad \text{(R22)}$$

In case a technology can be ramped up fast enough, the total upward reserve contribution of a technology may include both, online and offline reserves. The online upward reserve provided by such a technology could therefore be smaller than its total upward reserve contribution (R23 & R24).

$$\forall_{y,l,t,f=PrimReserveUp,r}: (\boldsymbol{MaxPrimReserveDown_{y,t,r}} \,\&\, \boldsymbol{MaxPrimReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}:$$

$$RateOfProductionByTechnology_{y,l,t,f,r} / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq PrimReserveUpOnline_{y,l,t,r} \quad \text{(R23)}$$

$\forall_{y,l,t,f=SecReserveUp,r}$:
$(\boldsymbol{MaxSecReserveDown_{y,t,r}}$ & $\boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq$
$\boldsymbol{MinStableOperation_{y,t,r}}$:

$$RateOfProductionByTechnology_{y,l,t,f,r}/\boldsymbol{CapacityToActivityUnit_{t,r}} \geq SecReserveUpOnline_{y,l,t,r} \quad \text{(R24)}$$

Further, the upward reserve provided by online plants is limited by their online capacity minus their power output (R25).

$\forall_{y,l,t,f,r}$: $ElectricityForTransmissionTag_{f,r} = 1$ &
$[(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ & $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) \geq$
$\boldsymbol{MinStableOperation_{y,t,r}}$ or
$(\boldsymbol{MaxSecReserveDown_{y,t,r}}$ & $\boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq$
$\boldsymbol{MinStableOperation_{y,t,r}}]$:

$$OnlineCapacity_{y,l,t,r} - RateOfProductionByTechnology_{y,l,t,f,r} /\boldsymbol{CapacityToActivityUnit_{t,r}} \geq PrimReserveUpOnline_{y,l,t,r} + SecReserveUpOnline_{y,l,t,r} \quad \text{(R25)}$$

Finally, the upward reserve provided by online plants is limited by their defined maximum contribution to the upward reserve (R26 & R27).

$\forall_{y,l,t,r}$: $(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ & $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) \geq$
$\boldsymbol{MinStableOperation_{y,t,r}}$:

$$OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxPrimReserveUp_{y,t,r}} \geq PrimReserveUpOnline_{y,l,t,r} \quad \text{(R26)}$$

$\forall_{y,l,t,r}$: $(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ & $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) \geq$
$\boldsymbol{MinStableOperation_{y,t,r}}$:

$$OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxSecReserveUp_{y,t,r}} \geq SecReserveUpOnline_{y,l,t,r} \quad \text{(R27)}$$

3.3.4.2 Maximum Changes in Online Capacities and Generation

It might not be desirable or realistic to allow the model to freely vary the online capacity of a technology from one time slice to another. Therefore, the analyst can define a maximum reduction of the online capacity from one time slice to another. Time slices which are linked to each other are defined by a tag. This tag equals one if a link exists and zero otherwise.

Note that a maximum reduction could be associated with any time slice combination. As such, it could be defined that the online capacity in a summer week day morning can only be reduced by ten per cent until lunch time. Further, it can as well be defined that the same holds true the other way round, i.e., that the online capacity during the morning is only allowed to be ten per cent lower than the online capacity during lunch time. A value of 0.1 for the maximum online capacity reduction would therefore limit the change of capacity from currently 100% down to 90%, or from currently 90% up to 100%.

In (R28), the online capacity in a time slice which is linked to another time slice is reduced up to its defined maximum. The online capacity of the other time slice has to be larger than this reduced capacity.

$$\forall_{y,l,ll,t,f,r}: \\ \boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1 \;\&\; \boldsymbol{TimeSliceLinkTag_{l,ll,r}} \neq 0: \\ OnlineCapacity_{y,ll,t,r} * (1 - \boldsymbol{MaxOnlineCapReduction_{y,t,r}}) * \\ \boldsymbol{TimeSliceLinkTag_{l,ll,r}} \leq OnlineCapacity_{y,l,t,r} \qquad \text{(R28)}$$

In case the online capacity of a technology is kept constant from one time slice to another, the electricity output may still vary between the minimum stable generation and the maximum output. It might as well be desirable to constrain the change in electricity output based on ramping characteristics, especially if time slices represent a rather short period of time within a specific day-type. Therefore, the analyst can as well define a maximum reduction of the generation. This reduction is entered as a percentage of the online capacity.

The electricity generation in one time slice which is linked to another time slice is reduced up to its defined maximum. The electricity generation in the other time slice has to be larger than this reduced generation (R29).

$$\forall_{y,ll,t,f,r}: \boldsymbol{ElectricityForTransmissionTag_{f,r}} = 1 \;\&\; \boldsymbol{TimeSliceLinkTag_{l,ll,r}} \neq 0: \\ (RateOfProductionByTechnology_{y,ll,t,f,r} - OnlineCapacity_{y,ll,t,r} * \\ \boldsymbol{MaxGenerationReduction_{y,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}}) \\ * \boldsymbol{TimeSliceLinkTag_{l,ll,r}} \leq RateOfProductionByTechnology_{y,l,t,f,r} \qquad \text{(R29)}$$

Note that if the maximum reduction is set to one (or larger) in (R28) and (R29), the left side of the inequalities would be negative. As the online capacity and the electricity generation on the right side are always equal or larger to zero, both inequalities would not be binding in this case.

4 Test Case

This section presents an application of the proposed code enhancements. All data applied is realistic and derived from the literature [49,306,368–377]. Further information on the input data is provided in Annex E.

However, the application is purely exemplary and the presented results just serve to showcase how investment dynamics are influenced by the consideration of flexibility requirements. This indicates the value of the code enhancements for later applications to real-world situations.

To emphasise its illustrative character, the application was deliberately designed not to represent a specific country or energy policy, but rather to investigate a simple system which serves to demonstrate the model enhancements. The system was set up to enable the model to choose between a limited set of pairs of technologies, which fulfil different required functions: (a) two based-load generation technologies (nuclear and coal); (b) two technologies which are, at least initially, used for peak-load generation (open-cycle and closed-cycle gas turbines) and (c) two 'carbon-free' technologies, one of which introduces increased variability into the power system (nuclear and wind).

4.1 Main Assumptions

The power system of the illustrative case study was assessed for a single region over the period from 2010 to 2040. Complying with current practice in long-term modelling, a limited number of time slices was chosen (refer to Section 1.4.1 of Part B). Each year was represented by one representative day for each season, split up in a day- and night-time period. Valuable insights might be gained from a more detailed analysis of the choice of time slices and scenarios. As this is rather a proof-of concept than a real-world case study, it was therefore considered to be outside of the scope of this application.

As suggested in Section 2.2.1 of Part B of this thesis, a half an hour time horizon was chosen to estimate primary reserve requirements and a four hour time horizon for secondary reserve. Reserve requirements were considered based on some of the metrics provided in that section and as outlined in more detail in Annex E. Electricity generation was modelled drawing on nuclear-, coal- and gas-fired power plants as well as wind power.

For combined and open cycle gas turbines (CCGT and OCGT), two sub-technologies each were entered. These sub-technologies represent power plants that will operate in one of two distinct states. One represents an operation close to the maximum capacity where only primary reserve can be provided. The other represents an operation at part-load with a reduced efficiency, allowing the provision of both primary and secondary reserve. During any year, the model can chose an optimal combination of these two system states. This allows modelling the varying efficiencies and fuel consumptions of gas turbines in more detail, given the large contribution of their fuel costs to the total costs [370]. Further, it enables a quick assessment of the type of reserve for which a gas turbine is primarily used for. In the following tables and graphs, the two sub-technologies are differentiated by the suffix '-fl' for full load, and '-pl' for part load.

A minimum renewable energy generation target of 20% in 2030 was imposed. It was assumed that the minimum generation would increase by 1% each year up until this target value. Further, the maximum CO_2 emissions of the power sector were limited to 225 million tonnes per year.

Four models were set up to assess this illustrative case study (Table 4). They serve to demonstrate the dynamics introduced through the added functionality. All draw on the same input data. However, each of these cases builds on, and adds functionality to, the previous model.

As further explained in Annex E, the sinking fund depreciation used in the core code of OSeMOSYS was replaced by a straight-line depreciation. Building on this adjustment, the option to choose between sinking-fund and straight-line depreciation was later integrated into the core version of OSeMOSYS as of 14 March 2013 [310].

Table 4
Model descriptions

Case Name	Description
1. Conventional Model	Based on the core code of OSeMOSYS without any increased functionality. A constant capacity credit of wind power was assumed.
2. Calculated Capacity Credit	The capacity credit of wind power was calculated within OSeMOSYS.
3. Secondary Reserve	Additionally, secondary reserve requirements were considered. Throughout a day-type, the online capacity of nuclear and coal-fired power plants has to remain constant. Cycling of technologies was constrained between the minimum stable generation and the maximum online capacity.
4. Primary and Secondary Reserve	Primary reserve was considered as well.
a) Limited Cycling of Nuclear	Within one day-type, nuclear power was only allowed to cycle in between 80% and 100% of its online capacity.
b) Increased Cycling of Nuclear	Nuclear power was allowed to cycle in between its minimum stable generation level and its online capacity.

4.2 Results

The following sections provide the main findings for each of these cases.

4.2.1 Conventional Model

In this model case, no reliability assessment was performed and the capacity credit of wind was entered as a constant. In a first estimate, it was set equal to the capacity factor of wind, which is 0.26. This simplistic assumption was made for comparison with the calculated capacity credit as presented in the following modelling set-up (refer to Section 4.2.2 of Part B). No reserve requirements were taken into account.

In the conventional model, some of the total wind and nuclear power capacities that are retired in 2015 and 2020 are not replaced by the same technology. Instead, the model chooses to invest in the cheaper coal-fired power plants (Fig. 16). Due to their higher capacity factor compared to wind power, a slight reduction of the total capacity can be observed in 2015. The renewable energy generation target enforces an increase in wind generation from 2016 onwards.

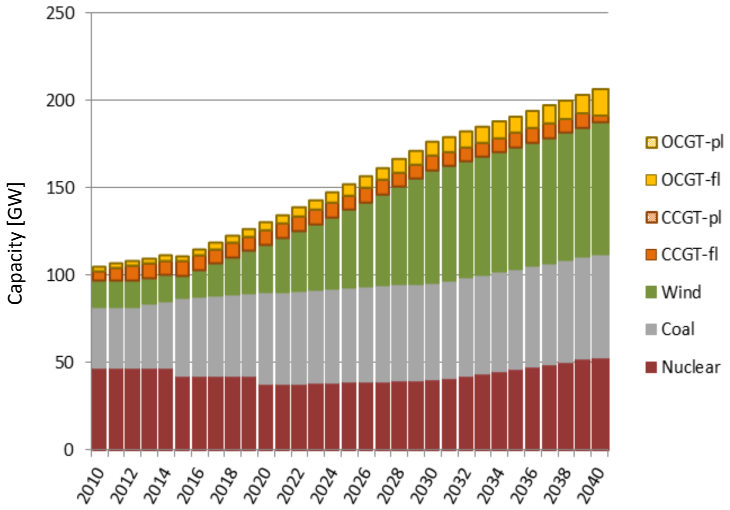

Fig. 16: Capacity mix in conventional model

The target generation share of 20% is reached in 2030 and maintained from thereon. Once this target is reached, most new capacity investments focus on nuclear energy, the only alternative to wind power with 'zero' CO_2 emissions. While the capital costs of nuclear power are higher, so is as well its availability (refer to Table 17 in Annex E). This makes it a more attractive investment to comply with the emissions target than wind power. Part-loaded gas turbines are not invested in. This is due to their lower efficiencies. Also their contribution to reserve services is not rewarded in this model case. This implies that when gas turbines produce electricity, all of it is assumed to be generated at full load with maximum efficiency. The total installed capacity amounts to 105 GW in 2010 and 207 GW in 2040.

The emission target of 225 million tonnes of CO_2 emissions per year is reached in 2023. It results in a basically constant annual electricity generation from coal-fired power plants in the remaining modelling period. However, coal generation varies significantly and unrealistically throughout one day (Fig. 17). For example, during every day in spring in 2010, coal-fired power plants are used to generate electricity during day-time, shut down during night time and again ramped up for the next day. Throughout the modelling period, both wind power and nuclear energy are dispatched up to their maximum availability. Only a share of the available gas turbines are used to generate electricity during times of peak-demand. They are mainly invested in to meet the required system reserve margin of 20%.

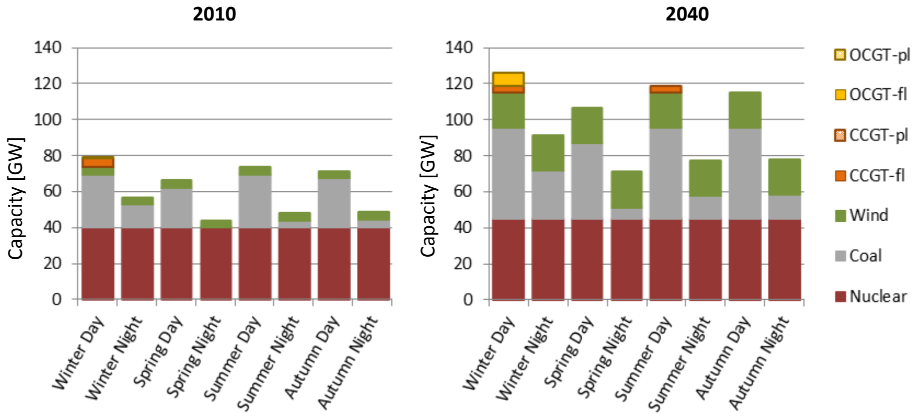

Fig. 17: Dispatch in conventional model

4.2.2 Calculated Wind Capacity Credit

As opposed to the conventional model, in this case the capacity credit of wind was calculated within OSeMOSYS based on penetration levels. This results in a maximum capacity credit of wind of 0.16, which decreases down to 0.12 over the modelling period. As expected, this demonstrates that aligning the capacity credit with the yearly capacity factor of 0.26 as done in the conventional model case would significantly overestimate the contribution of wind power to the system's reliability. Note that the reduction of the capacity credit just entails a lower contribution of wind towards the system reliability, and not a reduced annual generation per unit of capacity. Operating reserve requirements were again not considered.

The reductions in the capacity credit do not translate into reductions in investments in wind power. This is because wind power has to be invested in to comply with the renewable energy target. The decreased contribution of wind power to the overall system reliability is compensated by increased investments in open cycle gas turbines that, when called on, operate at full load. Compared to the conventional model, additionally 2 GW of fully loaded open cycle gas turbines are invested in 2010, which increases to 10 GW in 2040. All other capacities as well as the dispatch remain the same as in the conventional model case. Overall, this leads to a 5% increase in the total installed capacity (107 GW in 2010 and 217 GW in 2040). Open cycle gas turbines are chosen due to their cheap investment costs. Their high fuel costs are not an issue as they are rarely dispatched since they are just built as a system reserve.

4.2.3 Secondary Reserve

In this model case, secondary operating reserve requirements are considered. This and the following case draw on the enhanced model as described in Section 2.2.2 of Part B of this thesis. The wind capacity credit is again calculated within OSeMOSYS. Throughout a day-type, the online capacities of nuclear and coal-fired power plants were assumed to remain constant. This constrains any cycling to occur in between the minimum stable generation level and the online capacity. This was done to avoid that the model would potentially shut these plants down during night time and ramp them up again at day time during every day within one season.

In a more detailed power system model, considering additional technical detail like start-up costs and minimum down and up times would limit such cycling. Such detail is however commonly neglected in long-term energy system models. This is done to avoid mixed integer programming with on and off decision variables and due to their coarse temporal resolution. Limiting the change in the online capacity during one day-type is therefore an alternative which improves the accuracy of the modelled dispatch.

In this and the following model cases, the demand for operating reserve results in a system reserve margin[155] which is higher than its predefined minimum of 20% (in this case: 25% in 2010, 23% by 2040). Therefore, the total capacity is higher than in the previous cases. It amounts to 111 GW in 2010 and 221 GW in 2040. Simply implementing this higher reserve margin in the conventional model would result in the same total capacities. However, all additional capacities required to meet the reserve margin would come from open cycle gas turbines, i.e., the technology with the lowest investment costs. No other system

[155] Capacity credit of all power plants divided by load, minus one.

wide implications of providing these reserve services would be taken into account.

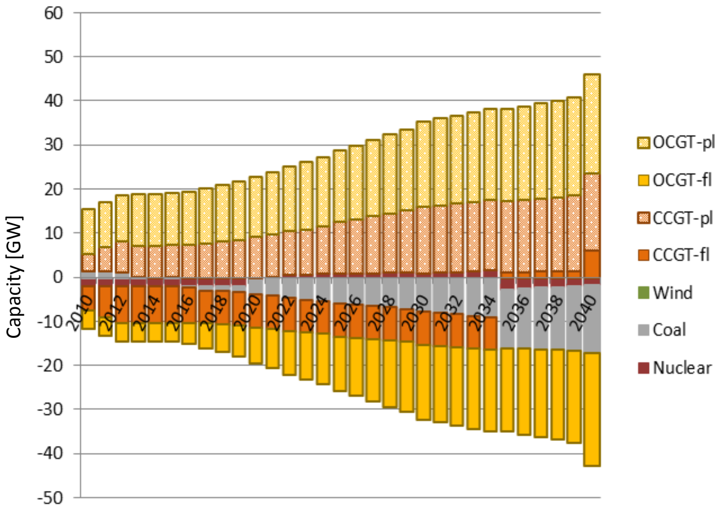

Fig. 18: Changes in capacity when secondary reserve is considered Compared to case with calculated wind capacity credit

Positive y-axis values: capacity additions
Negative y-axis values: capacity reductions

The most significant change as compared to the model case with the calculated capacity credit is the investment in gas turbines that, when running, operate at part-load, as shown in Fig. 18. In this figure, capacities in addition to the previous case (Calculated Wind Capacity Credit) are shown with positive and reduced capacities with negative y-axis values. Combined cycle gas turbines are mostly built to meet peak electricity demand and as well to provide some secondary upward reserve. Open cycle gas turbines are mainly invested in for the provision of secondary upward reserve. They are only dispatched for electricity generation during the time slice when peak demand occurs (Fig. 19). During all years, there is always more downward reserve available then required. Therefore, downward reserve requirements do not influence any investment decisions.

There are minor reductions in investments in coal-fired power plants from 2016 onwards (Fig. 18). These reductions become more significant once the emission target of 225 million tonnes of CO_2 emissions per year is reached in 2020. From 2020 onwards, coal-fired electricity generation decreases constantly. However, coal retirements in 2025 and 2030 are still almost completely replaced by new coal installations. This situation changes in 2035. Then, they are partly substituted by investments in combined cycle power plants operating at full load with maximum efficiency. These combined cycle power plants are dispatched up to their maximum available capacity during the peak demand time slices (right graph in Fig. 19). Overall, in 2040, this results in 15 MW equalling 26% less coal-fired power plants as compared to the case with the calculated capacity credit.

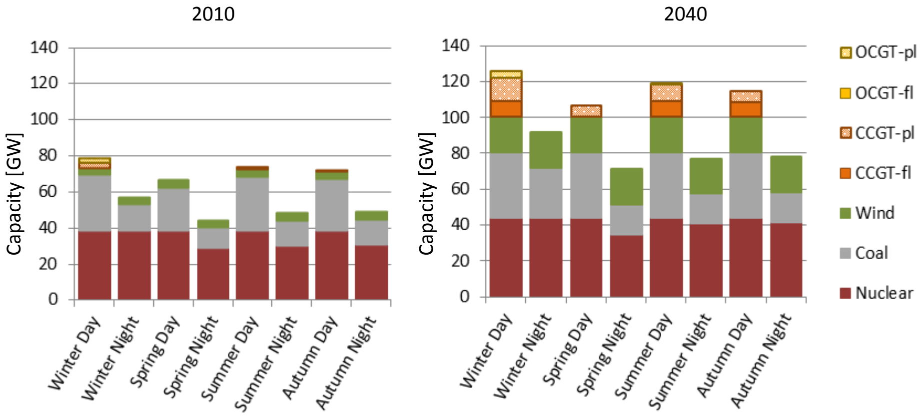

Fig. 19: Dispatch when secondary reserve is considered

As opposed to the previous case, nuclear is not constantly dispatched at its maximum available capacity any longer. This is because the introduced cycling constraints reduce the flexibility in dispatching coal-fired power plants. For example, the online capacities of coal during Spring Day limit the required minimum generation during Spring Night when lower demand occurs. This decreased flexibility of coal is compensated by the increased cycling of nuclear. The most extreme cycling of nuclear power occurs in 2034, when its output during Spring Night is reduced to 71%.

4.2.4 Primary and Secondary Reserve

Limited Cycling of Nuclear

In this model case, primary operating reserve requirements were included in addition to the secondary reserve demands. Further, it was assumed that within one day-type nuclear power would only be capable of cycling between 80% and 100% of its online capacity. In the model definition, this was implemented by setting the minimum (stable) generation to 80%.

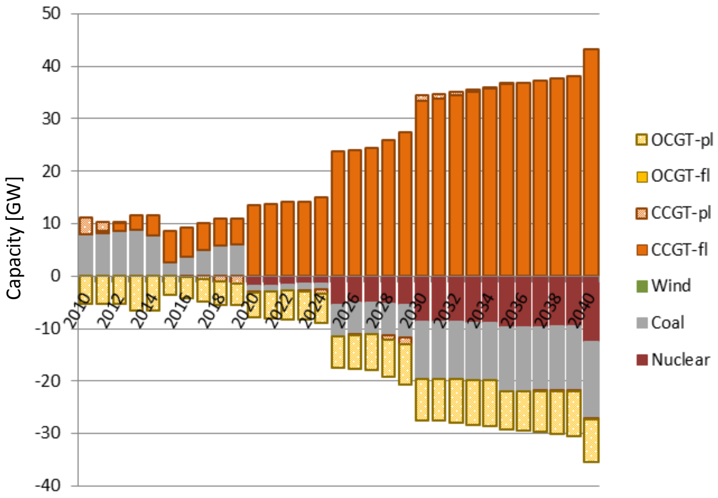

Fig. 20: Changes in capacity when considering primary and secondary reserve; Cycling of nuclear is limited Compared to case with secondary reserve only

Positive y-axis values: capacity additions
Negative y-axis values: capacity reductions

Additional power plants are required to meet the demand for primary reserve. Compared to the previous case, the total capacity therefore increases to 117 GW in 2010 and 228 GW in 2040.

In the first decade of the modelling period, more coal-fired power plants are invested in (Fig. 20). Yet, it is not economically efficient to dispatch all of the available capacity up until 2014. The reason for this 'overinvestment' in coal during the first years is its initially important role in providing primary reserve. Coal power plants always contribute to the primary upward reserve up to their technical maximum. In the first ten years during the periods of lower demands, coal and nuclear power plants are able to provide all of the primary reserve.

Up until 2014, coal power plants also provide secondary reserve. In the five years after the emission target is reached in 2020, coal investments are very similar to the previous case without primary reserve considerations (Fig. 20). Especially towards the later years, both coal and nuclear power plants cannot contribute significantly to meeting the increasing primary reserve requirements any longer. This results in lower investments in these technologies in the second half of the modelling period.

Throughout the modelling period, combined cycle power plants operating at maximum efficiency gain in importance in providing primary reserve. This is because of their rather high ramping rates. While open cycle gas turbine provide even better ramping rates, their associated greenhouse gas emissions and fuel costs are higher. Therefore, combined cycle power plants are dispatched throughout the year from 2020 onwards. The increasing role of combined cycle gas turbines constitutes the most significant change compared to the case with secondary reserve only. While investments in part-loaded open gas turbines decrease, they still have an important role to play in providing secondary upward reserve.

Within one day-type, most demand variations are compensated by the cycling of coal and combined cycle power plants (Fig. 21). Coal-fired power plants are using their full cycling capabilities for this purpose. While nuclear does not draw on its full cycling range for electricity generation, it uses its full range for the provision of reserve. Especially during periods of low demand, the power system provides just as much primary downward reserve as required. After 2016 the total secondary downward reserve exceeds the system's requirements.

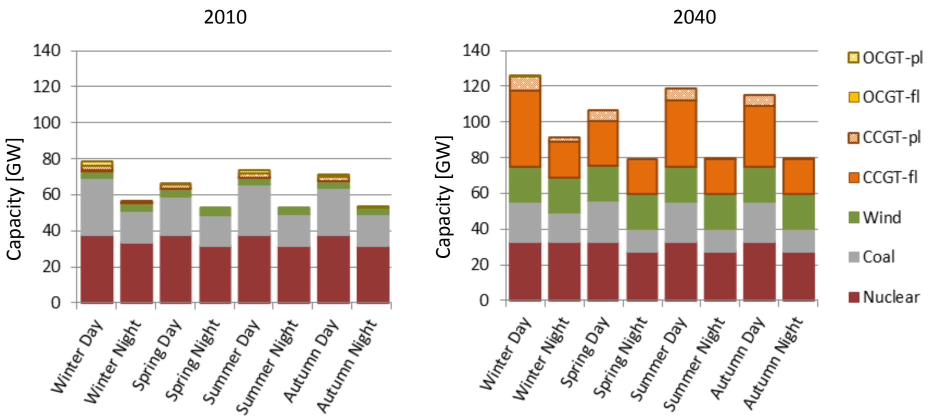

Fig. 21: Dispatch when primary and secondary reserve is considered; Cycling of nuclear is limited

Increased Cycling of Nuclear

In this model case, again primary and secondary reserve requirements were considered. Further, nuclear power plants were allowed to cycle between their minimum stable generation level of 50% up to their online capacity within a day-type. This corresponds to an advanced nuclear power plant design.

Changes to the case with limited cycling of nuclear are marginal during the first ten years (Fig. 22). Once the emissions target is reached in 2020, the increased cycling ability of nuclear power plants makes them more attractive. As their generation can be reduced during times of lower demand, coal-fired power plants may increase their output during such times. Given the higher contribution of coal towards the primary reserve, less combined cycle power plants are therefore required during such periods. In 2040, this results in 14% higher nuclear and 16% higher coal power capacities, and 20% lower capacities of combined cycle power plants operating at full load.

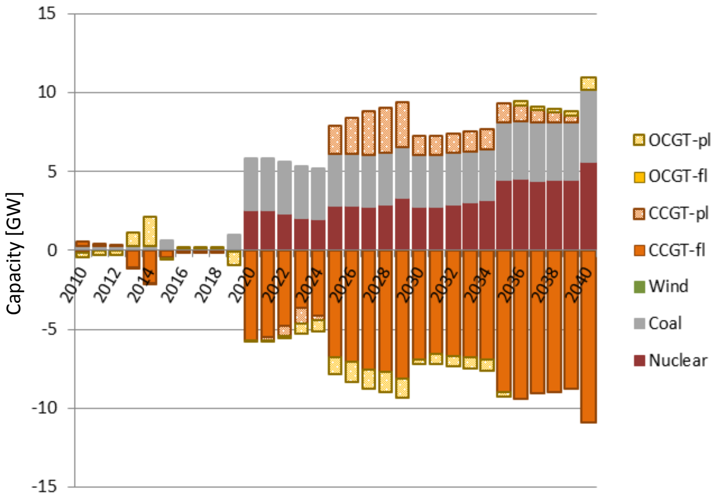

Fig. 22: Changes in capacity when considering primary and secondary reserve; Increased cycling of nuclear Compared to case with limited cycling of nuclear

Positive y-axis values: capacity additions
Negative y-axis values: capacity reductions

4.3 Discussion

Fig. 23 provides an overview of the capacity mixes in some of the model cases for the year 2040. In the conventional model case, gas-fired power plants contribute only 10% to the total capacity despite the high share of wind power. Almost all of the variability in demand is compensated by the unrealistically extreme cycling of coal-fired power plants. This situation does not change significantly once the capacity credit of wind is calculated by OSeMOSYS. This only results in a 4% higher capacity share of open cycle gas turbines to meet the system reserve margin.

Considering system security through the modelling of balancing requirements significantly improves the results. Coal is not cycled unrealistically any longer. Further, gas-fired power plants gain in importance in compensating the variability introduced by wind power. In the model case in which secondary reserve requirements were introduced, gas-fired power plants now provide 23% of the total capacity.

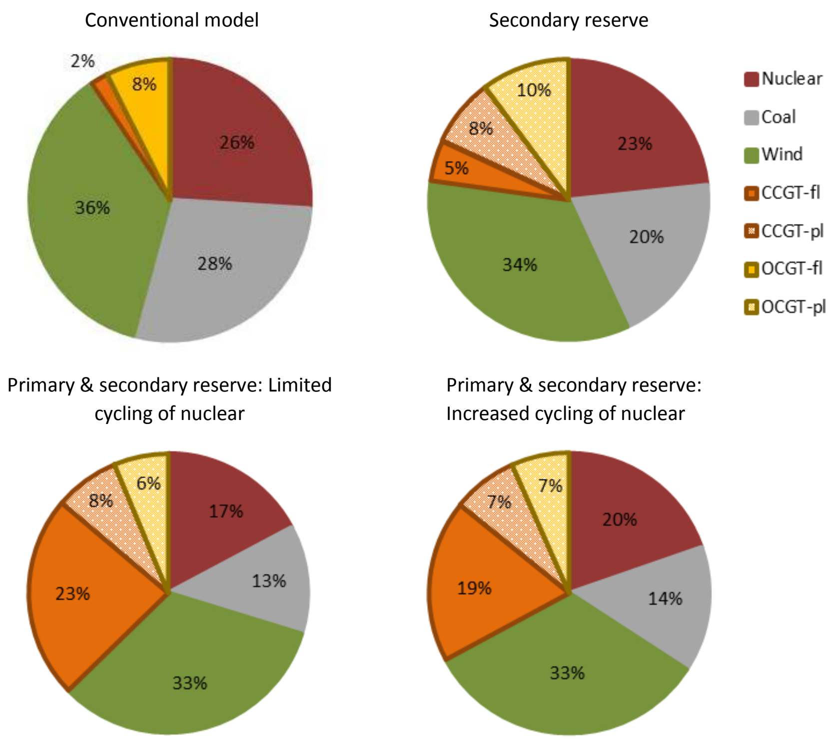

Fig. 23: Capacity mix in 2040 for selected model cases

Including primary reserve and limiting the cycling of nuclear power plants between 80% and 100% of their online capacity considerably limits investments in nuclear. Interestingly, the decreased flexibility of nuclear also affects coal-fired power plants: Nuclear power is the preferred option for the dispatch, given its low fuel costs. As it can only be cycled down to a limited extent within one day, less coal-fired power plants can come online during off-peak periods. The online nuclear and coal-fired power plants are not sufficient to provide all the primary reserve. This results in higher investments in combined cycle power plants.

Increasing the cycling ability of nuclear therefore results in increased investments in both, nuclear power and coal-fired power plants, and reduced capacities of gas-fired power plants. This increased flexibility comes at the cost of a reduced annual utilisation of nuclear power plants, which decreases from 78% to 72% over the modelling period. Power markets would need to value this increased flexibility to trigger the required increased investments in nuclear power despite the reductions in the capacity factor.

Due to the coarse temporal resolution, wind power is always dispatched whenever it is available. However, during some time slices wind power is as well used as a primary downward reserve. This is an indication that it would be curtailed if the temporal resolution was increased. Refer to Deane et al. [49] for a demonstration of the effects of increased temporal resolution on wind curtailment.

In addition to providing an unrealistic capacity mix, the conventional model underestimates the total power system costs (Fig. 24). Calculating the capacity credit of wind power with OSeMOSYS results in only 1% higher overall costs. This is because the cheapest technology is invested in to maintain the system reserve, regardless of its potential fuel consumption and its technical and environmental characteristics. Considering secondary reserve results in 3% higher costs than in the conventional model. The highest cost increase of +11% occurs when considering both primary and secondary reserve with a limited cycling capability of nuclear power. This is mainly due to the higher fuel costs of natural gas.

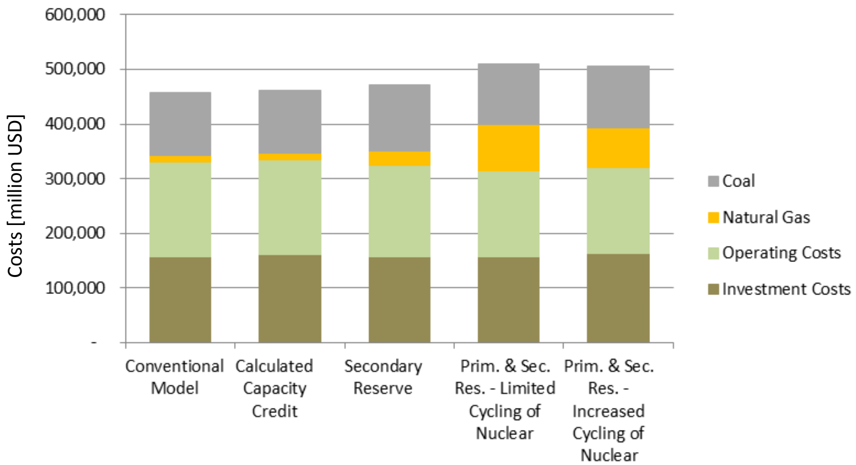

Fig. 24: Discounted power system costs 2010 – 2040

If applied to a real-world case, the model enhancements may provide valuable insights regarding the value of an increased flexibility of a technology. This could be achieved by comparing the total power system cost for two model runs with different technology parameters. For example, in this application the two cases with primary and secondary reserve could be compared to investigate the value of improved cycling characteristics of nuclear power generation.

The presented application just served as a proof-of-concept and did not represent a specific country. However, the comparison of the model cases demonstrated that the detail added through the enhancements significantly influences results. This indicates that national or regional models may underestimate the importance of flexibility within the power system if short-term variability is not considered. Policies informed by such models might therefore promote energy systems which do not ensure that expected reliability standards are met. Next, a real-world case study is presented.

5 An Irish Case Study

In preceding work by UCC [49], an operational power system model of Ireland (PLEXOS) was soft-linked with a long-term energy system model (TIMES) to assess the year 2020. This served to model the power system implications of the Republic of Ireland's 40% renewable electricity generation target [378]. The penetration rate of 40% was set in support of Ireland's 16% renewable energy target [315]. Given the detailed temporal resolution and representation of technical characteristics, soft-linking these models provides for improved dispatch results, thereby serving as a benchmark for the OSeMOSYS enhancements presented in this part of the thesis.

The Irish power plant capacities up until 2020 were largely determined by currently existing installations and planned extensions. Comparisons for 2020 therefore focused on the generation mix. The analysis was therefore extended until 2050 to investigate differences in the capacity mixes between various OSeMOSYS models. This gives an indication of how investment strategies and supportive policies might differ.

Table 5 provides an overview of the key parameters applied in these three modelling tools. Further background on the individual modelling tools is provided in Section 5 of the introduction of this thesis.

Table 5
Key parameters applied in the three modelling tools. Adapted from Deane et al. [49]

Parameters		Plexos	OSeMOSYS Enhanced	TIMES
Technical	Installed capacity	✓	✓	✓
	Input/output fuels	✓	✓	✓
	Heat rates/efficiencies	✓	✓	✓
	Min. stable generation	✓	✓	
	Up/down ramp rates/reserves	✓	✓	
	Min. up and down times	✓	*	
	Maintenance rates/availabilities	✓	✓	✓
	Repair time	✓		
Economic	Fuel costs	✓	✓	✓
	Emission costs	✓	✓	✓
	Variable O&M costs	✓	✓	✓
	Fixed O&M costs		✓	✓
	Start-up costs	✓	*	
Environmental	Emissions	✓	✓	✓

* Considered indirectly through cycling characteristics (see Section 2.2.2 of Part B)

First, Ireland's power system is briefly introduced and the soft-linking approach is explained in Section 5.2 of Part B of this thesis. Then, various increasingly detailed versions of OSeMOSYS models are presented, which are applied for comparison with TIMES-PLEXOS. The calculation of the capacity credit of wind is explained in Section 5.4 and some further code adjustments are introduced in Section 5.5. These are required to model Ireland's pumped storage hydropower plant and its varying contributions to the operating reserve in pumping and in generation mode. This is followed by an outline of the main driving assumptions of these models. Results are then presented in Section 5.7 for the year 2020 and in Section 5.8 for the analysis to 2050. These are then discussed in Section 5.9 of Part B.

5.1 Ireland and its Power System

Ireland's power system is characterised by a recent decrease in electricity consumption due to the recession. In 2008, a total of 30,190 GWh were generated, which reduced to 27,440 GWh in 2011 [369,379][156]. 80% of the generated electricity stemmed from fossil sources with negative implications for Irelands energy import dependence[157]. The most important renewable power source is wind, which contributes with 16% to the total generation. The remaining 4 % are met by hydropower, landfill gas, other biogas and biomass. Recent growth rates of renewables provide an indication of their expected importance in Ireland's future power mix: generation from renewable electricity sources increased by 30% from 4,108 GWh in 2009 to 5,429 GWh in 2011.

Ireland is connected to Wales via the East-West interconnector with a capacity value of 440 MW and to Northern Ireland. It relies on 100 MW from Northern Ireland. An additional North-South tie line is expected to come into operation in 2017. Northern Ireland itself is connected to Scotland via the Moyle Interconnector with an import capacity of between 410 – 450 MW. Due to a fault in one of the two cables, only 250 MW are currently available [381].

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[156] Almost 40% of all final electricity consumption occurs in industry. One third of the consumption is due to residential and about one forth due to commercial and public demand. The remainder comprises agricultural demand and, to a very limited extent, transport [380].

[157] Electricity generation contributes with one third to the total primary energy demand, 90% of which are met by energy imports [380].

5.2 Soft-linking a Long-term Energy Model with an Operational Power System Model

Soft-linking TIMES with PLEXOS required a reconciliation of the temporal resolution between the two models. In TIMES, day, night and peak times of a single characteristic day were modelled in each of the four seasons over the period 2005 – 2020. This results in 12 time slices. PLEXOS on the other hand was set up as a chronological, hourly model. The lowest common denominator was therefore one year. Soft-linking was implemented by feeding the power plant capacity mixes for 2020 as derived from the TIMES model into PLEXOS. PLEXOS then assessed the overall operational reliability and technical appropriateness of this particular capacity mix.

All models were subject to a common constraint which reflects Ireland's 40% renewable electricity generation target. In line with EirGrid and SONI [317], the technically acceptable instantaneous maximum wind share in the generation mix was limited to 70% of the load. Technical data such as efficiencies and emission factors as well as economic data such as fuel and carbon prices were consistently defined in both models. Additional data such as ramping rates and start-up costs was required for the power system model.

In this thesis, the soft-linked models are referred to as the TIMES-PLEXOS model. Several model runs were performed to demonstrate the effects of variations in wind availability, temporal resolution and technical detail. The applied methodology is described in detail in Deane et al. [49] and graphically represented in Fig. 25.

In this work, the most basic and most advanced TIMES-PLEXOS configurations were compared with OSeMOSYS:

1. **TIMES-PLEXOS Simple:** This model investigates the effects of increased temporal resolution. It runs at hourly intervals, but without any additional operational constraints. Outage calculations are based on Monte Carlo simulations. It is referred to as "Simple" in Deane et al. [49].
2. **TIMES-PLEXOS Enhanced:** This model additionally investigates the effects of increased operational detail. It builds on the simple set up, but considers start-up costs, minimum stable generation levels, ramping rates, and operating reserve requirements. It is referred to as "Reserve" in Deane et al. [49].

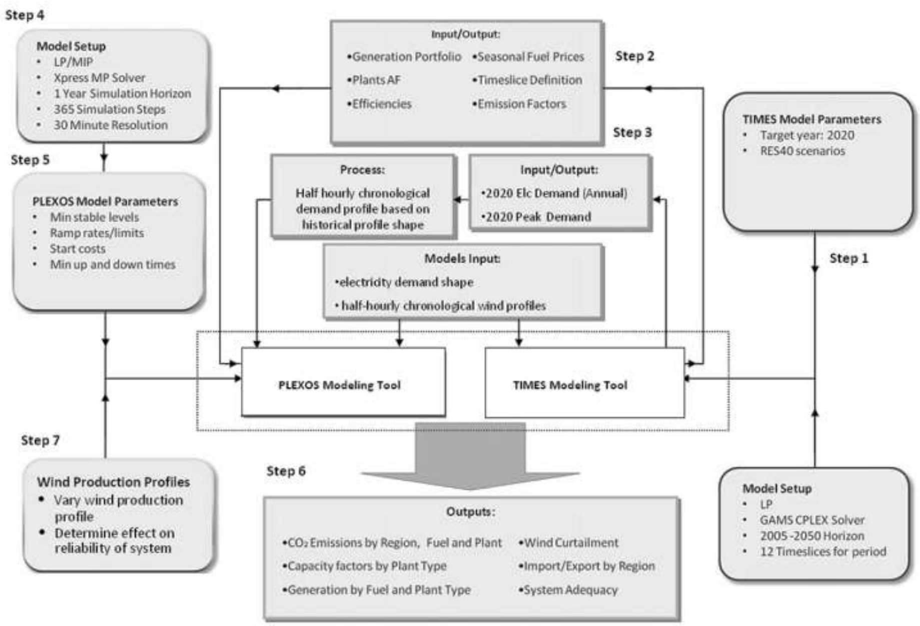

Fig. 25: Flow chart of soft-linking methodology [49]

Comparing OSeMOSYS to these two model configurations enabled a differentiation of the accuracy gains due to the hourly resolution in the simple TIMES-PLEXOS model from those due to additional operational detail as considered in the enhanced TIMES-PLEXOS model.

Input data and results from the stand-alone TIMES model [26] were used to configure the initial OSeMOSYS model.

5.3 Enhancing a Long-term Model

Several increasingly detailed OSeMOSYS models were set up for comparison with the soft-linked TIMES-PLEXOS models. As opposed to the soft-linked models, all OSeMOSYS models (like the stand-alone TIMES model) only consider 12 time slices and are based on less operational detail:

1. **OSeMOSYS Simple:** In a first model run, the core code of OSeMOSYS[158] was applied. It was slightly adjusted to better model Ireland's pumped storage hydropower plant. This set up is similar to the stand-alone TIMES model. As such, it is representative of conventional long-term energy system models without operational detail.
2. **OSeMOSYS 70% Wind:** This model run draws on the simple model, but uses a detailed wind availability assessment based on hourly data as additional input. This enabled a more accurate consideration of the 70% wind generation limit despite the low temporal resolution (refer to Section 5.6.1 of Part B). The results for 2020 were compared with those of the simple TIMES-PLEXOS model. This comparison serves to investigate the implications of the increased temporal resolution as applied with TIMES-PLEXOS versus the external data analysis as performed in the OSeMOSYS model.
3. **OSeMOSYS Enhanced:** This set-up considers the effects of increased operational detail. It builds on OSeMOSYS 70% Wind, but additionally includes some of the constraints of 'TIMES-PLEXOS Enhanced', i.e., operating reserve requirements, maximum contribution of individual power plants to meeting these reserve requirements and minimum stable generation levels.

Given the vintage structure of existing Irish power plants, new capacities already in the pipeline and projected low electricity demand growth, all models showed identical capacity mixes by 2020. Comparing results for 2020 between the various TIMES-PLEXOS and OSeMOSYS models therefore served to assess variations in their dispatch.

Investigating the implications on new capacity investment decisions required an extension of the modelling horizon. OSeMOSYS model runs were therefore set up until 2050, when most of the current power plants will be retired. The models could therefore freely invest in the most economic technologies while complying with the greenhouse gas emission reduction targets.

A succinct summary of the TIMES-PLEXOS and OSeMOSYS model runs is provided in Table 6.

[158] In its version of 2013-04-30 as available at www.osemosys.org.

Table 6
Summary of the main characteristics considered in the model set-ups

OSeMOSYS Simple	OSeMOSYS 70% Wind	TIMES-PLEXOS Simple	OSeMOSYS Enhanced	TIMES-PLEXOS Enhanced
• Uses the core code of OSeMOSYS, as available at osemosys.org	• External wind data analysis to ensure a max. wind penetration of 70%	• Comparable input data to 'OSeMOSYS 70% Wind' • Hourly, chronological simulation	• External wind data analysis • Min. stable generation • Reserve contribution • Operating reserve	• Hourly (wind power) simulation • Start-up costs • Min. stable generation • Ramp rates • Operating reserve

5.4 Capacity Credit Calculations

Section 2.1 of Part B of this thesis describes the OSeMOSYS implementation of an analytical formula by Voorspools and D'haeseleer [51] to estimate the capacity credit of wind power. As mentioned, this formula was integrated into OSeMOSYS to provide a first-order estimate in case of a lack of more detailed external reliability assessment. When developing the formula, data from the Irish Transmission System Operator was used for its calibration. Therefore reapplying it to Ireland was expected to provide rather accurate results, at least up until a penetration level of 30%, which constituted the upper end of the calibration range of the formula.

The Transmission System Operators (TSOs) of Ireland and Northern Ireland [381] provide an updated assessment of the capacity credit of wind in Ireland based on the half-hourly wind profile of 2009. This assessment was compared to calculations based on the analytical formula, using the following input data: a dispersion coefficient for Ireland of 0.33 as suggested by Voorspools and D'haeseleer [51]; a wind capacity factor of 31.7%; a reliability of conventional generation of 87%; and the 2009 peak load of 4,850 MW, which was aligned with data by the Irish TSOs [381].

The dependency of the capacity credit on the penetration rate is presented in Fig. 27 based on the assessment by the Irish TSOs and as calculated by the analytical formula. The two corresponding curves (solid and dashed line) show a similar slope up until a penetration rate of about 30%. However, the capacity credit is constantly about 6% higher when applying the analytical formula. This difference increases with penetration levels above 30%. When trying to adjust the input parameters of the formula to match the data provided by the Irish TSOs, a good fit up until a penetration level of 30% is achieved by reducing the capacity factor by 5% points (dotted line). There is however no justification for such a reduced capacity factor apart from trying to match the two curves.

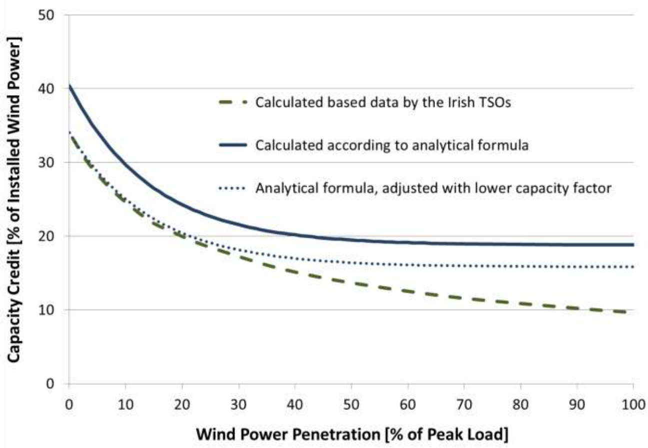

Fig. 26: Capacity credit of wind power

While no assessment of the quality of the results of the two approaches was made by the author, it can be assumed that the more detailed and country-specific reliability assessment provided by the Irish TSOs is also more accurate. As suggested in Section 2.1.1 in Part B of this thesis, the analytical formula was therefore not applied in this case study, but aligned with the capacity credit values derived from the data by the Irish TSOs.

5.5 Modelling Ireland's Pumped Storage Hydropower Plant

The modelling of storage within OSeMOSYS has been explained in detail in Section 2 of Part A of this thesis. The storage formulations described therein enable a consideration of various day-types and seasons and ensure continuity of storage levels across the year. Further, storage capacity expansions can be optimised. The broad applicability of these storage formulations comes at the expense of extended calculation times. It was however possible to simplify parts of the storage equations by adjusting them to the Irish case study.

Ireland's only pumped storage hydropower plant has capacity for about 1.24 GWh, or 4.2 hours of operation at full load. It is therefore operated in a daily cycle, i.e., the storage volumes are refilled every day. Therefore, only one specific day-type in a season had to be considered. Further, no storage capacity expansions had to be investigated.

Additional modifications were required to more accurately model the power plant's contribution to operating reserves. Within PLEXOS, pumped storage is modelled in detail distinguishing between pumping mode, spinning mode and generation mode. In OSeMOSYS, a simplified consideration of the storage behaviour was implemented:

1. Any pumping activities were considered as spinning upward reserve.
2. Up until 50 MW of spinning reserve can be provided in spinning mode by two out of the four turbines. This comes with a low minimum stable generation of 5 MW per plant.
3. Up until 120 MW of spinning reserve can be provided by at least two turbines in generation mode at a minimum stable generation level of 40 MW per plant. The other two turbines were assumed to be in spinning mode without providing any reserve.

2) and 3) were calculated in separate model runs with different input data, starting with mode 2) due to its favourable lower minimum stable generation level. If the power generation and reserve provision reached the limits of mode 2), the model would be reassessed in mode 3). Results are then presented for the mode which results in the lower total discounted costs, i.e., with the lower value of the objective function.

Refer to Table 7 in Section 5.6.1 of Part B for further technical characteristics of Ireland's pumped storage hydropower plant.

Algebraic Formulation

All code enhancements refer to OSeMOSYS in its beta version as of 2013.04.30, as downloadable via the OSeMOSYS website (www.osemosys.org). For a brief explanation of all indices used in the following algebraic formulations refer to Box 3 in Section 3.1. of Part B of this thesis. Additional indices are provided in Box 5. The model code corresponding to the following algebraic formulations is provided in Annex F.

Box 5: Additional Indices for Pumped Storage Hydropower

ls … Season, e.g., spring or winter

m … Mode of operation: Several input and output fuel combinations can be combined for a single technology by defining several modes of operation.

Box 6 introduces the additional input parameters for the calculation of the following enhancements.

Box 6: Parameters Used to Model Pumped Storage Hydropower

DaysWithinSeason$_{ls,r}$ – Number of days within a season.

StorageEfficiency$_{t,r}$ – Round trip efficiency, e.g., amount of energy available for discharge after charging one unit of energy.

StorageLimit$_{t,r}$ – Amount of energy which can be stored or discharged within a day.

StorageTag$_{t,f,r}$ – Equals 1 for the fuel stored by storage technologies and 0 for all other fuels and technologies.

TimeslicesInSeason$_{ls,l,r}$ – Set equal to 1 to assign a particular time slice to a single characteristic day within a season.

As mentioned, Ireland's pumped storage hydropower plant is operated in a daily cycle. This implies that at the end of every day the amount of water stored and discharged must equal. The right side of equation (SD1) calculates the amount of fuel which is stored within a day: Within one season, which is represented by one characteristic day, all the fuel stored (i.e., charged) by a storage technology is summed up over all time slices within that season. This has to equal the amount of fuel 'produced' (i.e., discharged) by the storage technology, divided by the round-trip storage efficiency. The storage tag ensures that only storage technologies and their related fuel are considered.

$$\forall_{y,ls,t,f,r}:$$

$$\sum_l ProductionByTechnology_{y,l,t,f,r} * \boldsymbol{TimeslicesInSeason_{ls,l,r}} / \boldsymbol{StorageEfficiency_{t,r}} * \boldsymbol{StorageTag_{t,f,r}} = \sum_l StorageCharging_{y,l,t,f,r} * \boldsymbol{TimeslicesInSeason_{ls,l,r}} \quad \text{(DS1)}$$

The maximum amount of fuel which can be produced by the storage technology is reached if the storage capacity is used up to its limit in every single day within a season. The actual production within one season has to be smaller than this maximum (SD2).

$$\forall_{y,ls,t,f,r}: \boldsymbol{StorageTag_{t,f,r}} = \mathbf{1}:$$

$$\sum_l ProductionByTechnology_{y,l,t,f,r} * \boldsymbol{TimeslicesInSeason_{ls,l,r}} \leq \boldsymbol{StorageLimit_{t,r}} * \boldsymbol{DaysWithinSeason_{ls,r}} \qquad \text{(DS2)}$$

These two equations have to be linked to the core code of OSeMOSYS. Equation (EBa4) calculates all fuel used by a technology, which is ultimately used in the core code to balance fuel use and production[159]. The amount of fuel used to charge the storage needs to be added to equation (EBa4). The corresponding change to the original equation is shown in red in ($EBa4_{rev}$). This modification ultimately ensures that all energy charged by a storage technology is as well produced by any of the other technologies. The parameter YearSplit defines the length of each time slice as a fraction of the year. The division by YearSplit is required to ensure the same units (i.e., energy per time) are used on both sides of the equation.

$$\forall_{y,l,t,f,m,r}: \boldsymbol{InputActivityRatio_{y,t,f,m,r}} \neq 0 \; or \; \boldsymbol{StorageTag_{t,f,r}} \neq 0:$$

$$RateOfActivity_{y.l.t.m.r} * \boldsymbol{InputActivityRatio_{y,t,f,m,r}} + StorageCharging_{y,l,t,f,r} / \boldsymbol{YearSplit_{y,l}} = RateOfUseByTechnologyByMode_{y,l,t,m,f,r} \qquad \text{(EBa4}_{rev}\text{)}$$

In the core code of OSeMOSYS, equation (CAa4) ensures that all technologies operate below their maximum available capacity throughout the year. The charging of a storage device needs to be added to this constraint, as shown in red in ($CAa4_{rev}$).

$$\forall_{y,l,t,r}: \boldsymbol{TechWithCapacityNeededToMeetPeakTS_{t,r}} \neq 0:$$

$$RateOfTotalActivity_{y,l,t,r} + \sum_f StorageCharging_{y,l,t,f,r} / \boldsymbol{YearSplit}_{y,l} \leq \boldsymbol{TotalCapacityAnnual_{y,t,r}} * \boldsymbol{CapacityFactor_{y,l,t,r}} * \boldsymbol{CapacityToActivityUnit_{t,r}} \qquad \text{(CAa4}_{rev}\text{)}$$

With these adjustments a daily electricity storage cycle can be modelled, assuming each season is represented by one characteristic day-type and storage

[159] In (EBa11) of the core code.

capacities remain constant. If the contribution of storage devices to operating reserve should be considered, some more adjustments are required.

A particularity of pumped storage hydropower is that it is not only able to provide primary operating upward reserve by increasing its electricity generation, but also by reducing any pumping and associated electricity consumption. Equation (EBa1) of the core code calculates the production of a fuel by a technology. For this application it is modified to exclude the production of primary upward reserve by storage devices and renamed to ($EBa1_{rev,a}$). Instead, for such devices ($EBa1_{rev,b}$) ensures that in addition to any conventional provision of the fuel primary upward reserve through a potential increase in the electricity generation, also any pumping activities are considered as operating reserve. Note that in the model both electricity generation and pumping is very unlikely to occur within the same time slice due to the low roundtrip efficiencies.

$$\forall_{y,l,f,t,m,r}: \boldsymbol{OutputActivityRatio}_{\boldsymbol{y,t,f,m,r}} \neq 0 \ \&$$
$$if \ \sum_{ff} \boldsymbol{StorageTag}_{\boldsymbol{t,ff,r}} = 1 \ then \ f \neq PrimPreserveUp:$$
$$RateOfActivity_{y.l.t.m.r} * \boldsymbol{OutputActivityRatio}_{\boldsymbol{y,t,f,m,r}} = RateOfProductionByTechnologyByMode_{y,l,t,m,f,r} \qquad (EBa1_{rev,a})$$

$$\forall_{y,l,f,ff=PrimReserveUp,t,m,r}: \boldsymbol{StorageTag}_{\boldsymbol{t,f,r}} = 1:$$
$$RateOfActivity_{y.l.t.m.r} * \boldsymbol{OutputActivityRatio}_{\boldsymbol{y,t,ff,m,r}} + StorageCharging_{y,l,t,f,r} / \boldsymbol{YearSplit}_{\boldsymbol{y,l}} = RateOfProductionByTechnologyByMode_{y,l,t,m,ff,r} \qquad (EBa1_{rev,b})$$

When modelling reserve requirements, the analysts can define a share of the reserve which has to be provided by spinning (i.e., online) plants. In (R25) as further described in Section 3.3.4 of Part B, the upward reserve provided by online plants is, amongst others, limited by their online capacity minus their power output. This constraint has to be revised to include any pumping for storage charging ($R25_{rev}$).

$\forall_{y,l,t,f,r}$: $ElectricityForTransmissionTag_{f,r} = 1$ & $[(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ & $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}$ or $(\boldsymbol{MaxSecReserveDown_{y,t,r}}$ & $\boldsymbol{MaxSecReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}]$:

$$OnlineCapacity_{y,l,t,r} - (RateOfProductionByTechnology_{y,l,t,f,r} - StorageCharging_{y,l,t,f,r} / \boldsymbol{YearSplit_{y,l}}) / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq PrimReserveUpOnline_{y,l,t,r} + SecReserveUpOnline_{y,l,t,r} \quad \text{(R25}_{\text{rev}}\text{)}$$

The primary upward reserve provided by online plants is further limited by their defined maximum contribution to the upward reserve (R26). Any storage charging is added to this limit to ensure pumping is not affected by this limit and may fully contribute to primary upward reserve provided by online plants.

Note that this might potentially imply that the reduction of pumping may happen in parallel to an increased generation of the turbines, i.e., that ramping rates of the turbines are unaffected by any pumping which might occur in a given moment. If the same waterways are used for pumping and generation, in reality a delay of a few minutes might occur until electricity generation may be ramped up due to the inertia of the water in the waterways when switching from pumping to generation.

While a similar constraint exists for secondary upward reserve, it was not modified as it was assumed that secondary upward reserve requirements will not substantially influence results. Modelling results confirmed this assumption, as there was always more secondary upward reserve available then required.

$\forall_{y,l,t,r}$: $(\boldsymbol{MaxPrimReserveDown_{y,t,r}}$ & $\boldsymbol{MaxPrimReserveUp_{y,t,r}}) \geq \boldsymbol{MinStableOperation_{y,t,r}}$:

$$OnlineCapacity_{y,l,t,r} * \boldsymbol{MaxPrimReserveUp_{y,t,r}} + \sum_f StorageCharging_{y,l,t,f,r} / \boldsymbol{YearSplit_{y,l}} / \boldsymbol{CapacityToActivityUnit_{t,r}} \geq PrimReserveUpOnline_{y,l,t,r} \quad \text{(R26}_{\text{rev}}\text{)}$$

With this last modification, OSeMOSYS will be able to consider the contribution of Ireland's pumped hydropower plant to spinning reserve.

5.6 Assumptions

5.6.1 Analysis to 2020

Special attention was paid to ensure that the assumptions in OSeMOSYS match those of the TIMES-PLEXOS models. This was required to ensure the comparability of the results between the different models. The OSeMOSYS models were therefore set up using the same data as specified in Deane et al. [49] for the year 2020. If more detail was needed, OSeMOSYS was aligned with the input data used in PLEXOS. TIMES data was only used to fill the remaining gaps. These included existing power plant capacities and their scheduled extensions during the years 2009 – 2019 as well as investment costs. A 5% discount rate was applied in all model runs.

The demand profile in OSeMOSYS was derived from the half-hourly chronological demand profile applied in PLEXOS. In PLEXOS, the 2020 profile was aligned with historical data from 2007. The profile of that year was expected to be representative of 2020. This is because 2007 was not yet affected by the economic recession, whose effects on the demand profile of 2020 were assumed to be negligible. In line with the TIMES demand, the PLEXOS demand was scaled to represent the generation requirement of 29.8 TWh and the peak generation of 4.9 GW. The exact same 12 time slices defined in TIMES were used to calculate the demand in each time slice in OSeMOSYS. As the demand in each time slice is based on hourly averages, this results in a lower peak demand of 4.3 GW in OSeMOSYS.

As compensation, a rather high system reserve margin of 27% was applied. This reserve margin ensured that at least a 10% capacity reserve is available on top of the 'actual' TIMES-PLEXOS peak demand. In parallel, upward spinning and replacement reserve requirements of 440 MW each were applied in set-ups considering operating reserve (OSeMOSYS Enhanced). Apart from pumped storage hydropower, spinning reserve was defined as reserve provided by power plants which are online and generate electricity. In contrast, replacement reserve was defined as an additional reserve provided by all online and offline thermal and hydropower plants up to their available capacity.

Table 7 provides an overview of the power plant data used for the optimisation of the dispatch in 2020.

Table 7
Power plant data used for the dispatch optimisation in 2020

Power Plant Type	Capacity [MW]	Efficiency [%]	Maximum availability factors [%]	O&M cost [€/MWh]	Fuel costs [€/GJ]	CO_2 factor [kg/GJ]	Number of plants [-]	Min. stable generation [MW/plant]	Min. stable generation [% of cap.]	Max. spin. reserve [MW/plant]	Max. spin. reserve [% of cap.]
CC	1,422	47.5	87.0	0.04	4.40	56.1	4	150	42.2	60.0	16.9
CC - new	1,664	55.1	90.0	1.53	4.40	56.1	4	220	52.9	50.0	12.0
Gas	200	40.0	87.0	2.05	4.40	56.1	1	110	55.0	20.0	10.0
Coal	840	39.5	87.0	0.04	2.90	95.0	3	180	64.3	50.0	17.9
Peat	347	41.5	87.0	0.04	1.10	110.6	3	80	69.2	40.0	34.6
Distillate oil	496	38.0	87.0	2.05	4.00	77.4	5	10	10.1	10.0	10.1
Biogas	22	33.5	87.0	0.04	4.70	56.1	1	5	22.7	0.0	0.0
Waste	21	25.0	87.0	2.56	0.30	85.9	1	5	23.8	0.0	0.0
Wind onshore	4,305	100.0	31.7	0.00	0.00	0.0	1	0	0.0	0.0	0.0
Hydro power	234	100.0	25.5	0.00	0.00	0.0	16	2	13.7	1.9	12.8
Pumped storage	292	70.0	89.0	0.00	0.00	0.0	4	5	3.4	25.0	17.1

The wind availability in each time slice was derived from the hourly wind profile of 2008, which was applied in PLEXOS to model the year 2020. With its average capacity factor of 31.7% it is close to the annual average of the period 2002 – 2009, which varied between 29.1% – 34.7% [382]. A recent analysis of the integration of renewables in Ireland identified a maximum 'inertialess penetration' of 60% – 80% of the net load [317]. The analysis considered issues such as frequency, reactive power, voltage as well as transient stability. In line with its recommendation, the maximum share of wind was limited to 70%.

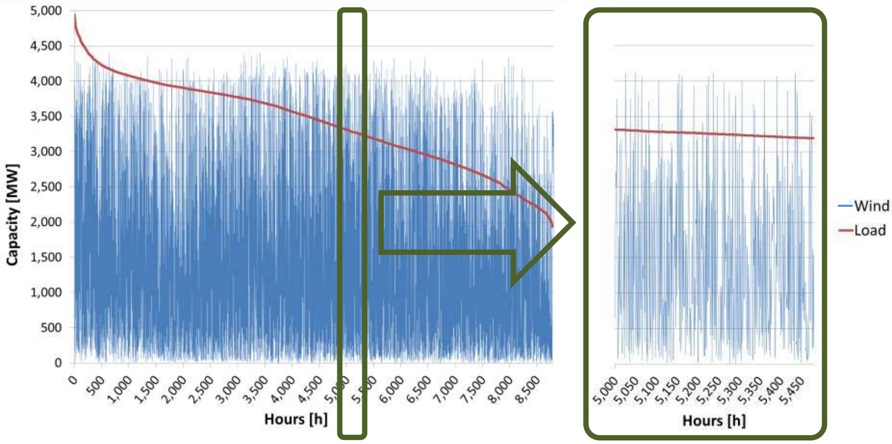

Fig. 27: Load duration curve with wind availabilities in 2020

While higher wind peaks can be observed around the evening electricity peak hours of fall and winter, in general significant peaks occur at any load level (Fig. 27). The average available wind was calculated for each of the 12 time slices considered in the stand-alone TIMES model and the simple OSeMOSYS set up. Mathematically, wind peaks were therefore levelled out and the maximum wind contribution limit of 70% was unrealistically easy to fulfil. However, when analysing the hourly wind and half-hourly demand data, wind penetration rates above the 70% limit occur in 1799.5 hours of the year. In the 'OSeMOSYS 70% Wind' and 'OSeMOSYS Enhanced' set-ups, the hourly wind profile was consequently reassessed. The wind availabilities were reduced if required to comply with this constraint before calculating the average wind availabilities for each time slice. Curtailment of wind power was therefore implicitly considered through this data analysis.

5.6.2 Analysis to 2050

When extending the analysis to 2050, the electricity demand growth rates and CO_2 emission constraints were aligned with those of the scenario 'CO2-80' as described in Chiodi et al. [26]. Complying with EU greenhouse gas emission targets, this scenario includes emission reductions of 80% as compared to 1990 levels. Other technical data was aligned with the Irish TIMES model. The first year of operation of existing power plants were aligned with Platts [383] and power plant lifetimes with IEA et al. [306]. The models were allowed to reinvest in all existing power plant types as well as new designs to compensate retirements and meet demand growth. Table 8 and Table 9 show the relevant capacity related techno-economic data.

Table 8
Power plant data for reinvestments in existing power plant types

Power Plant Type	Investment Costs [EUR/kW]	O&M cost [€/kW/a]	Life-time [a]
CC	800	10.0	30
CC - new*	669	27.4	30
Gas	900	20.0	30
Coal**	1,642	42.6	40
Peat	1,420	40.0	40
Distillate oil	400	30.0	30
Biogas	800	20.0	30
Waste	800	80.0	40
Wind onshore	1,200	10.0	25
Hydro power	2,500	10.0	80
Pumped storage	4,000	10.0	80

* Aligned with estimations by the IEA [183], CC-new built from 2030 onwards was assumed to have an efficiency of 63%.

** In line with the long-term Irish TIMES model [26], new coal capacity additions operate with a lower minimum stable operation level of 48% of the installed capacity.

Investments in biogas, waste and peat were only allowed to compensate retirements. Total capacity additions for coal, onshore wind and hydropower were limited to 2,850 MW, 2,500 MW and 5 MW respectively. Yearly capacity additions for solar, onshore and offshore wind were limited to 300 MW each.

Table 9
Power plant data for investments in new power plant types

Power Plant Type	Max. Cap. Additions [MW]	Efficiency [%]	Maximum availability factors [%]	Investment Costs [EUR/kW]	Life-time [a]	O&M cost [€/kW/a]	O&M cost [€/MWh]	Fuel costs [€/GJ]	CO_2 factor [kg/GJ]	Min. stable generation [MW/plant]	Min. stable generation [% of cap.]	Max. spin. reserve [% of cap.]
Solar	5,000	100.0	9.6	2,200	25	10.0	0.00	0.0	0.0	0	0.0	0.0
Wind offshore	5,000	100.0	35.0	2,100	25	15.0	0.00	0.0	0.0	0	0.0	0.0
Coal with CCS	1,200	51.4	87.0	2,000	40	38.4	0.04	2.9	9.5	200	33.3	17.9
Gas with CCS	872	63.0	87.0	1,313	30	38.4	1.53	4.4	5.6	223	51.0	12.0
IGCC	2,850	38.1	87.0	2,366	30	59.8	1.53	2.9	74.5	136	47.7	12.0
OCGT	1,760	33.3	87.0	598	30	18.0	0.04	4.4	56.1	15	17.0	16.9
Biomass	360	40.3	87.0	900	40	80.0	2.56	2.9	0.0	41	34.2	0.0

As outlined in the previous section, considering the 70% wind constraint required an external analysis of the input data. Due to the change in wind power capacities over the years, an iterative process had to be applied when extending the analysis until 2050. First, the yearly capacity investments in onshore and offshore wind were calculated with OSeMOSYS. Then, an external analysis of the yearly wind and load profiles was performed to comply with the 70% wind constraint. For every year, the hourly wind profiles of onshore and offshore wind were reduced if needed and the average wind availability in each time slice was recalculated and updated in OSeMOSYS. A new OSeMOSYS run was then performed and the new wind capacity expansions were compared with the previous ones, which were updated if needed until convergence was achieved.

5.7 Results for 2020

Results of the simple OSeMOSYS model were first compared with those of the stand-alone TIMES model. The annual electricity generation by fuel type for 2020 proved to be very similar in the two models. This showed that the Irish power system was consistently represented in the two models. Due to the low temporal resolution, the wind penetration limit of 70% is never reached in the simple OSeMOSYS model. This is despite an installed wind capacity of 4.3 GW and a lowest load of 2.7 GW during the summer night time slice. Compared to the most accurate enhanced TIMES-PLEXOS model, over 20% of the yearly generation is not attributed to the correct power plant types in the simple

OSeMOSYS model. The dispatch of the main power plant types in the various OSeMOSYS and TIMES-PLEXOS model runs is illustrated in Fig. 28.

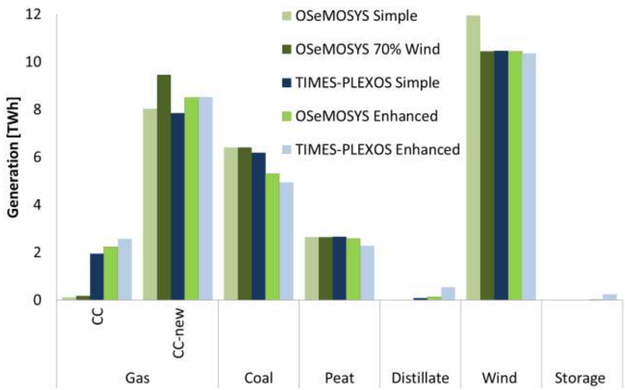

Fig. 28: Annual generation of the modelled power plant types in 2020
OSeMOSYS results in shades of green, TIMES-PLEXOS results in shades of blue.

The lower wind generation in the OSeMOSYS 70% Wind set up comes very close to the enhanced TIMES-PLEXOS model. It is largely compensated by an increased generation by new combined cycle gas turbines (CC-new). This overestimates their contribution compared to the TIMES-PLEXOS model runs. The less efficient combined cycle gas turbines (CC) are still barely dispatched. Otherwise, the results of the 70% Wind model are very close to the simple TIMES-PLEXOS model. However, in both of them too much coal is dispatched compared to the most complex model set up (TIMES-PLEXOS Enhanced).

Applying the enhanced OSeMOSYS model which considers operating requirements significantly improves the results. Coal is now an important source of spinning reserve at the price of a reduced electricity output. Also gas-fired power plants contribute to the operating reserve. Compared to the 70% Wind set up, the provision of reserve in the enhanced OSeMOSYS model reduces the dispatch of new combined cycle turbines. On the other hand the provision of spinning reserve forces less-efficient older combined cycle turbines to operate above their minimum stable generation level. This increases their electricity output.

While much less than in the enhanced TIMES-PLEXOS model, the previously unused pumped storage hydropower plant gets dispatched in the enhanced OSeMOSYS set-up. The enhanced TIMES-PLEXOS model was able to reflect the important peaking ability of distillate fuel-fired power plants. This operational detail did not show up in the enhanced OSeMOSYS model. Most likely this is due to the omitted start-up costs and its limited temporal resolution: as mentioned earlier, using average loads for the 12 time slices results in a lower peak demand in the OSeMOSYS models.

Overall, the results of the enhanced OSeMOSYS model are very close to the more complex enhanced TIMES-PLEXOS model. The sum of the absolute differences in the dispatch of all power plants types amounts to 1.5 TWh, or 5% of the total generation (Table 10). This constitutes a 77% reduction of the difference identified when comparing the simple OSeMOSYS with the enhanced TIMES-PLEXOS model.

Table 10
Sum of absolute differences of the dispatch of all power plant types in 2020 as compared to the enhanced TIMES-PLEXOS model

Absolute Difference	OSeMOSYS Simple	OSeMOSYS 70% Wind	TIMES-PLEXOS Simple	OSeMOSYS Enhanced
[TWh/a]	6.4	5.3	2.9	1.5
[% of Yearly Generation]	21.4	17.6	9.7	5.0

The total yearly CO_2 emissions of the enhanced TIMES-PLEXOS model amount to 11.29 Mt. Coincidentally this is almost the same value as calculated by the simple OSeMOSYS model. Total emissions are also very similar in the remaining model set-ups, varying at maximum by 5%. However, large differences occur when looking at the emissions from individual power plant types (Table 11). These are especially large for the less efficient combined cycle power plants (CC) and for the coal-fired power plants, due to the changes in the dispatch as outlined before. The enhanced OSeMOSYS model comes closest to the results of the enhanced PLEXOS model when looking at the sum of the absolute differences.

Table 11
Differences in CO_2 emissions in 2020 [Mt] as compared to the enhanced PLEXOS model

Power Plant Type	OSeMOSYS Simple	OSeMOSYS 70% Wind	TIMES-PLEXOS Simple	OSeMOSYS Enhanced
CC	-1.05	-1.03	-0.27	-0.15
CC-new	-0.18	0.35	-0.24	-0.01
Gas	-0.01	-0.01	0.00	-0.01
Distillate	-0.38	-0.38	-0.32	-0.29
Coal	1.19	1.19	1.01	0.24
Peat	0.34	0.34	0.34	0.27
Waste	0.06	0.06	0.00	0.06
Sum of Absolute Values	**3.20**	**3.35**	**2.18**	**1.03**

5.8 Results until 2050

When extending the OSeMOSYS analysis until 2050, the actual generation of electricity is rather similar between the individual OSeMOSYS set-ups (Fig. 29). This is not surprising: the year 2020 was characterised by existing power plant types and the model did not have much freedom to invest in new capacities. In 2050, all of the power plants existing in 2020 are retired, apart from around 100 MW of hydropower. The model could therefore freely invest in expanding capacities to ensure the most economic dispatch based on the level of detail provided in each model set-up.

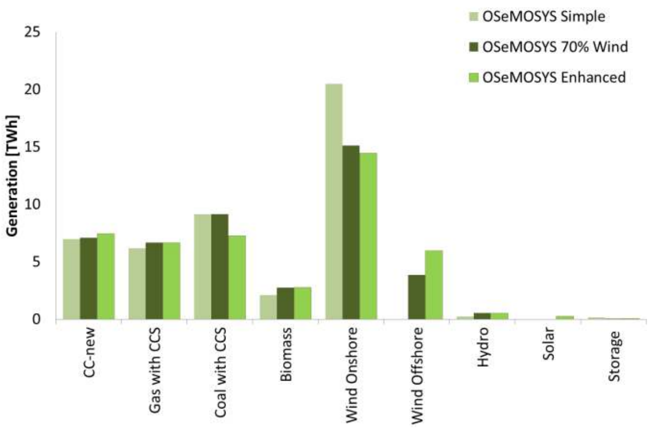

Fig. 29: Annual generation of the modelled power plant types in 2050

The biggest differences occur in wind power generation, which remains an attractive option to comply with the CO_2 emission reduction targets. When the 70% wind constraint is taken into account, the reductions in wind power generation during wind peaks cannot be compensated by additional capacity investments in onshore wind to increase the generation during periods of low wind. This is due to limitations in the allowed yearly capacity additions. The reductions are therefore largely compensated by investments in offshore wind power. Further, less coal-fired power plants with carbon capture and storage are dispatched in the enhanced model. This is because some of it is held back for the provision of spinning reserve.

Capacity investments vary considerably between the different OSeMOSYS set-ups. The capacity mix of the enhanced OSeMOSYS model throughout the modelling period is provided in Fig. 30. Towards the end of the modelling period, the emissions constraint triggers capacity investments which focus especially on low greenhouse gas emitting generation options: combined cycle gas turbines, wind power, and gas- and coal-fired power plants with carbon capture and storage. Also distillate oil-fired power plants are invested in and provide an important source of spinning reserve during many years.

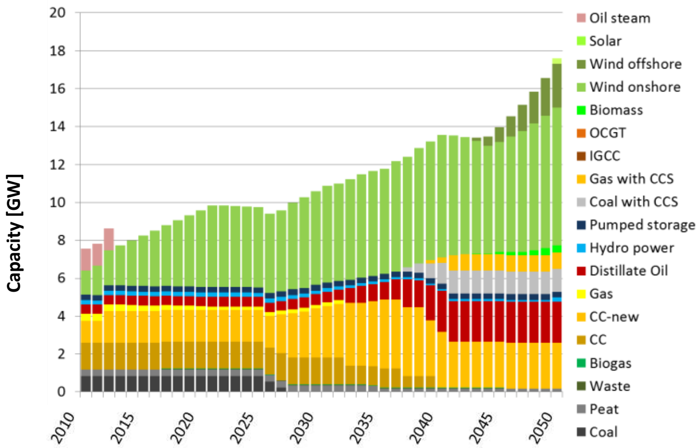

Fig. 30: Optimised capacities based on enhanced OSeMOSYS model

Several differences can be noticed when comparing the capacities illustrated in Fig. 30 to the other OSeMOSYS set-ups (Table 12). In the simple model, investments in combined cycle gas turbines are significantly underestimated, as their contribution to the operating reserve is not valued in this set-up[160]. Instead, more distillate oil is invested in, mostly to comply with the reserve margin of 27%. Overall, much less wind is invested in. Due to its higher availability when not considering the 70% wind constraint in the simple OSeMOSYS model, less wind capacities are required to comply with the emission targets.

Table 12
Deviation of power plant capacities from enhanced OSeMOSYS model

OSeMOSYS Simple								
Power Plant Types	**Unit**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Biomass	**MW**	0	0	0	0	0	-111	-84
CC-new	**MW**	0	0	-698	-971	-502	-502	-502
Coal with CCS	**MW**	0	0	0	0	45	0	0
Distillate oil	**MW**	0	0	667	779	564	564	564
Gas with CCS	**MW**	0	0	0	0	-295	-100	0
Hydro power	**MW**	0	0	0	0	0	0	-140
Peat	**MW**	0	0	0	161	161	161	161
Solar	**MW**	0	0	0	0	0	0	-300
Wind onshore	**MW**	0	376	533	479	479	479	103
Wind offshore	**MW**	0	0	0	0	0	-782	-2,282
Σ |Plant Capacity Deviations|	**MW**	0	376	1,897	2,390	2,046	2,699	4,137

OSeMOSYS 70% Wind								
Power Plant Types	**Unit**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Biomass	**MW**	0	0	0	0	0	81	0
CC-new	**MW**	0	0	-307	-664	-479	-479	-479
Coal with CCS	**MW**	0	0	0	0	105	0	0
Distillate oil	**MW**	0	0	320	633	410	410	410
Gas with CCS	**MW**	0	0	0	0	-68	0	0
Hydro power	**MW**	0	0	0	0	0	0	0
Peat	**MW**	0	0	0	42	42	42	42
Solar	**MW**	0	0	0	0	0	0	-300
Wind onshore	**MW**	0	0	-170	-170	-170	-170	-170
Wind offshore	**MW**	0	0	0	0	0	-782	-883
Σ |Plant Capacity Deviations|	**MW**	0	0	797	1,510	1,274	1,964	2,284

When considering the 70% wind constraint, combined cycle power plants are again less important than in the enhanced model and associated investments are lower. Despite the consideration of the 70% wind constraint in both models, in

[160] However, as mentioned their generation in the different model set-ups is similar.

the OSeMOSYS 70% Wind set-up less wind is invested in than in the enhanced OSeMOSYS model.

It may seem counter-intuitive that considering operating reserve requirements in the enhanced model results in more wind power installations. However, the provision of operating reserve forces coal-fired power plants with carbon capture and storage to operate below their maximum available capacity. To comply with carbon reduction targets, this reduced generation is mostly compensated by new wind power installations in the enhanced model. Some of the capacity reductions of combined cycle power plants in the OSeMOSYS 70% Wind model are compensated by increased investments in distillate oil-fired power plants, mostly to comply with the reserve margin.

Table 13
Total capacities, discounted costs and emissions based on enhanced OSeMOSYS model

OSeMOSYS Enhanced	Unit	2020	2025	2030	2035	2040	2045	2050
Total capacity	GW	9.84	9.40	10.89	11.79	13.57	13.96	17.60
Discounted costs	10^6 USD	390.4	318.2	467.8	347.6	375.3	243.9	150.6
Emissions	kt of CO_2	11,416	11,059	9,390	9,078	7,467	5,333	3,200
Emission limit	kt of CO_2	16,000	13,867	11,733	9,600	7,467	5,333	3,200

The key results of the enhanced model are summarised in Table 13 and comparisons with the other models are provided in Table 14. In the enhanced model the emission limit only becomes binding in the last decade of the modelling period. In earlier years, the total CO_2 emissions vary significantly between the individual set-ups in some years. In 2030, their deviation to the enhanced set-up amounts to 14.4% in the OSeMOSYS 70% wind set-up.

The total capacities in 2050 are 14.1% lower in the simple model and 7.8% lower in the set-up considering the 70% wind constraint. The deviations increase significantly when relating the sum of the absolute capacity difference within each power plant type to the total installed capacity: In the simple model, 23.5% of the total capacity in 2050 is attributed to other power plant types than in the enhanced model. This value still amounts to 13.0% when considering the 70% wind constraint. The OSeMOSYS Simple and OSeMOSYS 70% Wind set-up calculate lower overall discounted costs of 6.2% and 2.2% respectively. Looking at yearly costs, higher variations occur. They amount to up to 40.5% in the simple set-up and 15.2 % in the OSeMOSYS 70% wind set-up.

Table 14
Deviation of capacities, discounted costs and emissions from enhanced OSeMOSYS model

OSeMOSYS Simple	Unit	2020	2025	2030	2035	2040	2045	2050
Total capacity	%	0.0	4.0	4.6	3.8	3.3	-2.1	-14.1
$\frac{\Sigma\ \lvert\text{Plant capacity deviations}\rvert}{\text{Capacity OSeMOSYS Enhanced}}$	%	0.0	4.0	17.4	20.3	15.1	19.3	23.5
Discounted costs	%	-9.0	40.5	-11.3	-4.0	-5.8	-21.5	-14.3
Emissions	%	-1.3	-7.6	-14.4	-5.4	0.0	0.0	0.0

OSeMOSYS 70% Wind	Unit	2020	2025	2030	2035	2040	2045	2050
Total capacity	%	0.0	0.0	-1.4	-1.3	-1.2	-6.4	-7.8
$\frac{\Sigma\ \lvert\text{Plant capacity deviations}\rvert}{\text{Capacity OSeMOSYS Enhanced}}$	%	0.0	0.0	7.3	12.8	9.4	14.1	13.0
Discounted costs	%	-2.3	-1.9	-0.2	-3.0	-9.1	-15.2	-3.9
Emissions	%	3.5	0.3	-1.3	2.5	0.0	0.0	0.0

5.9 Discussion

The Irish case study has demonstrated that results of conventional long-term energy system model might show a significantly different dispatch to those being soft-linked to operational power system models. This is due to different temporal resolution and technical detail with regard to short-term variability of supply and demand. While soft-linking will ensure the most accurate results regarding the generation mix, this requires setting up and maintaining two separate models: a long-term model which focuses mainly on optimising the capacity expansion and an operational model which assesses the dispatch. As there is no overall optimisation across the two models, the identified capacity investments may not present the most economically efficient future technology mixes.

Some of the limitations of long-term models can be addressed through a more thorough external analysis of available data as well as by adjusting model input parameters accordingly. Others may be addressed by integrating operational aspects into the long-term capacity expansion optimisation. For example, 95.0% of the dispatch results of the enhanced OSeMOSYS model matched those of soft-linked models with a 700 times higher temporal resolution. This constitutes a significant improvement to a conventional long-term model set-up, where only 78.6% of the dispatch results matched. Ignoring short-term variability of supply and demand was shown to underestimate the overall investments required, and resulted in a sub-optimal investment in individual generation technologies: In the simple OSeMOSYS model, up to 23.5% of the total capacity was assigned to different power plant types as compare to the enhanced model.

As a next step, this analysis may be taken further by assessing the economic implications of market design. In particular it may be of interest to investigate the potential benefits of interlinking national markets to enable the trading of primary and secondary reserve services.

6 Conclusion

OSeMOSYS was extended and improved to consider the implications of variability in demand and generation on system adequacy and security. If omitted, long-term energy models may clearly underestimate the importance of flexibility within the power system, as demonstrated by both a test case and the Irish case study. If policies were derived from such long-term models, they might therefore promote energy systems which do not ensure that expected reliability standards are met.

An underestimation of flexibility requirements may as well be observed in reality: especially in 'energy-only' electricity markets, dispatchable technologies will face more volatile and on average lower electricity prices and capacity factors. This is due to the increasing shares of renewable electricity generation [384]. The profitability of investments in such dispatchable technologies will therefore decrease and retired capacities may not be replaced. Further, especially capital intensive investments will face increased difficulties to secure financing in the more volatile environments. However, the applications provided in Part B of this thesis have shown that dispatchable power plants have an important role to ensure the system's adequacy and security. Markets may face a gap between the need for flexibility and the incentives to invest in flexible technologies [83]. The economic and technical evaluation of this gap demands better modelling tools.

Through its system-wide focus, OSeMOSYS may help to highlight this gap. It may help derive corrective energy targets and investment strategies valuing all sources of flexibility within the energy system. The proposed model extensions are not limited to the power sector or to specific regions. For example, flexibility in the transportation sector through electric vehicles could be considered. In the heat sector combined heat and power plants or shiftable electric heating demands could be modelled. Further, OSeMOSYS does not necessarily rely on extensive time-series data or linkages with dispatch models. Yet, if available, it provides the flexibility to enable easy incorporation of such additional levels of detail. While the enhancements were presented for OSeMOSYS, their potential implementation in other long-term models such as TIMES or MESSAGE are expected to provide comparable improvements.

While such long-term models provide an optimal mix of technologies, a separate suite of models may assess how to best design markets and regulatory frameworks which trigger these optimal investments. The optimised technology mix as derived from OSeMOSYS may serve as an input to these shorter-term electricity market simulation and dispatch models. These models may help to identify an efficient mix of policy instruments such as carbon taxes or capacity payments to ensure that investments come closer to an optimum as derived from models like OSeMOSYS.

Part C
Integration Between Resource Systems

Climate, Energy, Water and Land-use Systems (CLEWS) are highly interlinked. Effective resource management requires a consideration of these linkages, especially when assessing climate change mitigation and adaptation measures. Yet, most related decision making occurs in separate institutional entities, informed by relatively disconnected assessments of the individual resource systems.

Part C presents and demonstrates the added value of an integrated analytical assessment approach. It considers various interdependencies and interactions between CLEWS with a focus on the energy system. Given its exposure to climate change and its integrated agricultural and energy policies, the small island developing state of Mauritius was identified as a useful case study. Several scenarios to 2030 were defined and analysed to demonstrate the tensions around the CLEWS nexus. Results from an assessment of the energy system with no modelled linkages to land-use and water systems are first presented. These are then compared to corresponding results from an integrated CLEWS assessment. This comparison helps to highlight important dynamics that would have been overlooked without such a systems approach. As an example, the added value of this approach is clearly demonstrated when rainfall reductions are taken into account, and where future land-use changes might occur.

Section 1 explains the importance of considering resource linkages before presenting a brief background on Mauritius and key findings of the CLEWS study. The methodology applied to assess the relevance of considering resource linkages is presented in Section 2. Scenarios are described in Section 3 and results are presented in Section 4. The added value of the CLEWS approach is synthesised at the end of that section. Part C concludes in Section 5 by highlighting conditions under which the benefits of an integrated CLEWS approach are likely to justify the additional effort required. An overview of key power plant input data is provided in Annex G.

1 Resource Integration and Mauritius

1.1 Rationale for Considering Resource Integration

Globally, the most basic human needs rely on the availability of few key resources. These include: water for drinking; water and land for food production; and energy for services like lighting, cooking and heating. An aspect all of these resources have in common is that they are – depending on the context – constrained in some way:

- In the last century, water use has increased more than twice as much as the global population growth rate, and water scarce areas keep expanding [385]. Currently, 780 million people lack access to drinking water sources which are protected from contamination [386] and 1.2 billion people are affected by physical and 1.6 billion by economic water shortage [387].
- Further, close to 870 million people are undernourished and 2.5 million children die each year from malnutrition [388]. At the same time, the food price crises in 2007 – 2008 caused a 'global rush for land' by capital-rich countries to secure agricultural imports [389].
- 1.3 billion people lack access to electricity and 2.6 billion people do not have clean cooking facilities at their disposal [1]. Further, current energy use is not in line with efforts to curb climate change within a 2 °C increase.

Therefore, an efficient management of these resources is a matter of urgent priority. As the pressure on these resources tends to increase globally, so do efforts to access and secure them, often leading to tensions in areas where they are scarce. Such tensions may be due to diverging priorities on how resources should be used. At a national level, they may be due to a dependency on resource imports. The prospects of climate change may exacerbate related stresses. This is due to the potential changes in rainfall and in the availability of arable land, which may be accompanied by increases in energy demand, e.g., for cooling. Examples for political stresses which are related to resources include tensions regarding the use of the river Nile [390,391], deforestation of the Amazon rain forest and its implications for climate change [392], or gas exports from Russia to Europe via the Ukraine in 2009 [16,393].

Any single one of these resources might cause stresses to secure their accessibility. Even more complex situations may evolve when they are interrelated. For example, future rainfall reductions in Mauritius would affect the water availability on this water stressed island, e.g., for hydropower generation and agriculture. Maintaining agricultural production requires an increased electricity generation for groundwater pumping for irrigation. Meeting this increased electricity demand and compensating the lower hydropower production requires additional generation by other power plants. Increasing the generation of fossil fuel-fired power plants increases the country's import dependency and greenhouse gas emissions. The interrelations observed locally in Mauritius are exemplary of those observed at a global scale.

70% of all water use is due to agricultural practices. But also electricity generation may require water. For example, up to 450,000 litres of cooling water may be required to produce one megawatt hour from nuclear power [1]. Energy is required for the withdrawal, distribution and treatment of water, including its desalination, which requires up to 5.0 kWh per cubic meter of water [394]. Currently, 24 billion cubic meters are desalinated per year globally. Further, biofuel targets may require 27 million hectare of additional agricultural land for their production in 2020 and may cause agricultural prices to increase by 30% [395]. Agriculture requires energy for cultivating, harvesting and processing crops. For further examples of such linkages between resource systems refer to work by Bazilian et al. [396].

Government structures and the associated division of responsibilities and priorities do not favour the integrated approach required to capture these linkages. Historically, related decision-making is often based on fragmented assessments of CLEWS resources and interactions between all resource systems are rarely taken into account [64]. Pollitt et al. [54] thoroughly maps tools used for integrated assessments. From an energy modelling perspective, integration hardly ever goes beyond a consideration of greenhouse gas emissions or biomass as a fuel for energy generation (e.g., as considered by Føyn et al. [55], Kannan and Strachan [56], Zhu et al. [57], Li et al. [58], Chen et al. [59], Möller and Lund [60], and Silva Herran and Nakata [61]). Campana et al. [62] went one step further by interlinking a water demand model with models representing a PV pumping system and Dubreuil et al. [63] incorporated elements of a water system model into an energy model.

A more holistic assessment was provided by Hermann et al. [64], which focused on the intensification of agriculture in Burkina Faso to help ensure future food production. The study indicated the importance of an integrated CLEWS approach when designing strategies in support of sustainable development.

Recognising the importance of capturing resource linkages, a CLEWS study on Mauritius is presented in Part C of this thesis to assess the added value of the CLEWS approach. Mauritius was identified as an ideal case study given its diverse climate, its growing water stresses, and its focus on reshaping agricultural land-use and decreasing fossil fuel imports. Further, Mauritius has a robust data set on the use of its resources, e.g., via the website of the Central Statistics Office [397]. As a small island, it also has conveniently defined system boundaries. The choice of Mauritius allowed building on previous work, which identified important CLEWS dynamics for Mauritius [398].

1.2 A Brief Background on Mauritius

The Republic of Mauritius is an archipelago of volcanic origin. It is situated in the Indian Ocean, 950 km east of Madagascar[161]. Its population amounts to 1.2 million inhabitants. With a population density of 668 people per km^2, it is the most densely populated country in Africa [399–401].

1.2.1 Economy

Mauritius is classified as an upper-middle-income country by the World Bank and as a small island developing state by the UN. Its economy is primarily based on services, which contribute 69% to the GDP. 27% of GDP are generated in industry including sugar processing. About 90% of the sugar produced is exported to the EU. Sugar represented 11% of total domestic exports in 2009 [402–405].

The country's economic and social progress is potentially under threat from external shocks. In 2009, an EU decision came into effect which cut the

[161] If not indicated otherwise, all data mentioned in Part C refers to the main island of Mauritius. Small surrounding islets as well as the neighbouring island of Rodrigues have not been included in the analysis. Their total area constitutes less than 10% of the total area of Mauritius (in total: 2,040 km^2) [399].

guaranteed sugar import price by 36% compared to 2006 price levels. Further, Mauritius imports coal and liquid fuels to meet 83% of its energy needs. It is therefore very vulnerable to rising and volatile global energy prices. Increased energy security and diversifying income from exports are key policy concerns [406–410].

In the wake of the reform of the EU sugar import regime[162], the government has formulated several measures to refocus agriculture. This is reflected by a shift from the farming of sugar cane to food crops. Further, since 2004, several sugar cane mills have started to produce ethanol. The target production of 30 million litres from molasses, either for domestic blending with gasoline or export, is therefore well in reach [400,412–417].

1.2.2 Climate, Agricultural Land-Use and Water

Mauritius has a sub-tropical maritime climate with an average annual temperature between 22 – 33 °C. Although it is relatively small with an area of 186,500 ha, its rainfall patterns are diverse and characterised by its topography. They are strongly dependent on elevation, proximity to the coast, and position relative to the prevailing winds and mountain ranges. Yearly averages may vary from as low as 750 mm in the western areas up to over 4,000 mm on the central plateau. Summer, lasting from November to April, receives two-thirds of the yearly rain [399,418,419].

These rainfall patterns are reflected in diverse agricultural conditions and result in extensive water transportation needs for irrigation. Full control irrigation increased from 12,000 ha in 1970 to 19,900 ha in 2010. More than 90% of this irrigated area is used for sugar cane production. Sugar cane is currently processed by six sugar producing factories, each with its dedicated cropland. Overall, 34% of the total area of Mauritius is cultivated [400,420].

Water demand per capita amounts to 221 l/capita/day. 63% of all water consumption can be attributed to agriculture[163]. While the agricultural sector currently meets its water demand mainly with surface water, over half of all

[162] The EU decision to reduce its guaranteed sugar import prices was taken to comply with its commitments within the World Trade Organization (WTO). Mauritius was considered as one of the countries suffering most from this reform [411].

[163] Utilisation of water for hydropower is not taken into account.

other water demand is met through extraction from boreholes[164]. Increasing this ground water use would be problematic: abstractions have reached saturation levels in large parts of the country with aquifers being at risk of sea water intrusion. This can especially be an issue in the northern and eastern coastal areas and during dry spells. While Mauritius is increasingly becoming water stressed, water conservation measures, wastewater treatment and desalination are becoming popular. For example, hotels are obliged to provide related provisions since 2005 [400,408,421–423].

1.2.3 The Energy System

Mauritius imports all of its petroleum products as well as coal. It uses only limited amounts of domestic renewable energy resources. These include fuel wood, wind power, hydropower and biomass – especially bagasse, a by-product of sugarcane processing. Bagasse accounts for 93% of the energy content of all domestic energy resources and is used for co-generation of heat and electricity at sugar factories [408,424,425].

Over the past decade, Mauritius' dependence on energy imports has grown from approximately 1,100 ktoe in 2000 to about 1,500 ktoe in 2010. The corresponding share of energy imports has increased from 11% of the total import bill in 2000 to 18% in 2010. During the period of peak oil prices in 2008 it rose to even 21% [408,419,426–428].

Electricity generation utilises 96% of all coal imports. The remainder is used by the manufacturing industries. Gasoline, diesel and aviation fuel are the three main transportation fuels. Overall, the transport sector accounts for 54% of all demand for petroleum products, while 26% are used for electricity generation [408].

In 2010, 2,689 GWh of electricity were generated. Thermal power plants, including the incineration of bagasse, contributed with 96% to the total electricity generation. Hydro and wind power provided the remaining 4%. The peak demand in 2010 was 404.1 MW. The generation fuel mix has been evolving over time with a major shift from fuel oil to coal. Of the 778 ktoe of fuel inputs used for power generation in 2010, coal comprised 51%, oil products 25% and bagasse 23% [408,426].

[164] Again, hydropower is excluded.

1.2.4 'Medine' and 'F.U.E.L.'

In the Mauritius case study, special attention was paid to the sugar cane processing plants 'Medine' and 'F.U.E.L', where ethanol production was introduced in some scenarios. Medine is situated in the more water stressed western part of Mauritius, some 15 km south-west of the capital Port Louis. In 2010, it processed the sugar cane of 4,600 ha of land. This corresponds to 8% of the total area in Mauritius where sugar cane is harvested. The by-product bagasse is currently used to generate heat and electricity for its own use and for export to the national grid. Its current electricity generation capacity is 6 MW [420,429].

F.U.E.L. is located about 20 km to the east of Port Louis. In 2010, it processed the sugar cane of 13,800 ha, corresponding to 24% of the total area harvested. It currently produces electricity from both, bagasse and coal, at a maximum capacity of 27 MW. Like at Medine, waste heat from bagasse is used for sugar cane processing. With 1.4 million tonnes, the sugar cane production of both Medine and F.U.E.L. amounts to 30% of the total production of Mauritius. The combined electricity generation of 167 GWh provides 7% to the total generation [420,429].

1.3 Contextual Work

In line with the long-term energy strategy of Mauritius [406], a CLEWS study was undertaken to investigate increases in local bio-ethanol production and the implication for land-use, energy and water systems, taking climate change into consideration. This section presents a concise summary of the key findings of this overall CLEWS study[165], before demonstrating the added value of the CLEWS approach in the following sections. Results were compared to a reference scenario, where current agricultural practices are maintained and no ethanol is produced locally.

The study showed that transforming the two sugar-processing plants Medine and F.U.E.L. to produce second generation ethanol will decrease the countries import dependence (left graph in Fig. 31). When introducing this type of

[165] The author of this thesis contributed to this CLEWS study through an assessment of the energy system and its linkages with other resource systems as outlined in the Chapter Publications at the beginning of this thesis.

ethanol production, both sugar and bagasse are converted to ethanol. Previously, this bagasse was used to generate electricity. Coal-fired power plants make up for the short-fall, thus increasing coal imports. Regarding the energy balance, this increase in coal imports is by far compensated by the reductions in petroleum imports due to the locally produced ethanol.

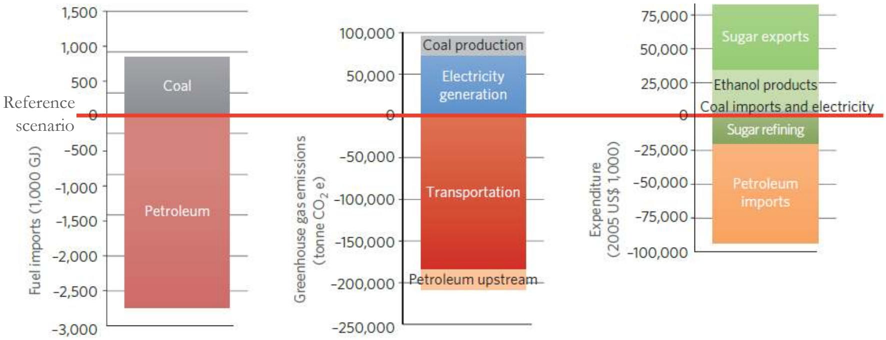

Fig. 31: Second generation ethanol production in Mauritius compared to business as usual – Selected dynamics for 2030

Positive values indicate increases compared to business as usual and negative values indicate decreases.

Despite this increased reliance on coal for electricity generation, overall tailpipe and upstream greenhouse gas emissions are reduced due to the introduction of carbon neutral ethanol generation (graph in the middle of Fig. 31). The reduced income from sugar exports and the costs for ethanol production and electricity generation are outweighed by reduced expenses for sugar refining and, most importantly, petroleum imports (right graph in Fig. 31). Overall, total expenditures can be slightly reduced when introducing second generation ethanol production.

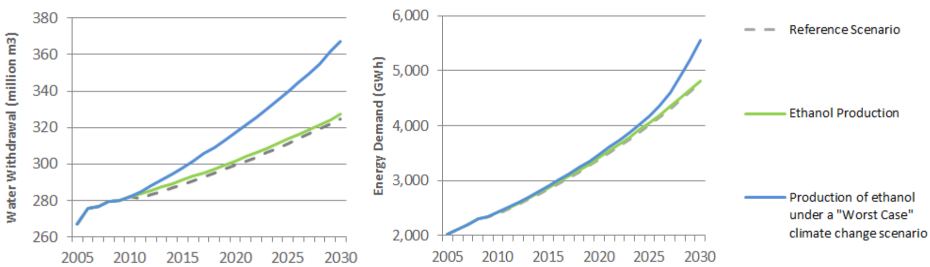

Fig. 32: Water withdrawals and energy demand

When considering climate change, the presented dynamics get more pronounced. The implications for water withdrawals and energy demand over the modelling period are presented in Fig. 32. While water reservoir levels are able to recover from extractions in the reference scenario, considering climate change results in their depletion, especially in the worst case scenario (left graph in Fig. 33). This is due to additional water demands for desalination, irrigation and ethanol processing. Their implications for electricity demand are presented in the middle of Fig. 33. Overall, greenhouse gas emissions increase significantly (right graph in Fig. 33) as compared to the ethanol production scenario without climate change (graph in the middle of Fig. 31).

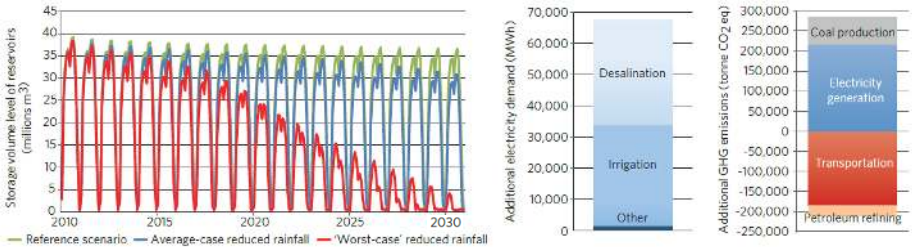

Fig. 33: Implications of considering climate change

Conceptually, the four main finding of the work on this CLEWS case study were that:

i. Such integrated assessments do not require the development of any new modelling tools. Existing resource models based on cost, mass and thermodynamic energy balances have proven their adaptability to enable a consideration of the linkages between the resource systems they represent.
ii. The effort involved in setting up such interlinked models is considerable. Most likely not one single entity will be able to deliver such an assessment due to the various fields of expertise required.
iii. Consequently, the time involved from initiating such a model to presenting an interpretation of its results may not match the timeframe of some policy making processes.
iv. Considering resource interdependencies with a CLEWS analysis will enable valuable insights into a range of topics. Conflicting objectives of resource policies, trade-offs and synergies may be difficult to identify and potentially impossible to quantify without such an integrated approach.

1.4 Transitioning from Energy to Multi-resource Modelling

While the presented results indicate the relevance of the CLEWS approach, the question was raised to what extent findings would have looked differently if no resource integration was taken into account. In the following sections, the CLEWS case study on Mauritius is therefore reassessed to quantitatively demonstrate the added value of such an integrated CLEWS approach. This is done by comparing conclusions derived from an energy model with those of an integrated CLEWS approach.

2 Methodology

Most decision and policy making related to land-use, energy and water systems occur in disconnected institutional entities with little, if at all, coordination or communication [52]. Therefore several scenarios were first analysed with a focus on the energy system and without taking explicit linkages between land-use, energy and water systems into account. Rainfall reductions based on publicly available climate model data were considered as an external input value to estimate hydropower availability for scenarios considering the effects of climate change [430,431]. This initial set up is outlined in Fig. 34 of Section 2.2 of Part C of this thesis and referred to as the **'Current Practice'** approach.

Next, the same scenarios were re-assessed considering these linkages by using the integrated **'CLEWS approach'** as shown in Fig. 35 in Section 2.3 of Part C. This approach draws on the following individual well-tested and specialised resource models.

2.1 Modelling Tools

Climate: External climate models were not set up as an integral part of this assessment. Instead, selected General Circulation Models (GCM)[166] and their corresponding climate projections were used to derive temperature and rainfall

[166] Including the following models: CGCM2 (C2A2, C2B2), CSIRO (CSA2, CSB1, CSB2), ECHAM (EHA2, EHB2) and HadCM3 (H3B1, H3B2, H3A1).

assumptions, which were applied to the other resource models [430,431]. Greenhouse gas emissions were accounted for in the energy model, but not fed back into the climate models as they on their own were not assumed to affect the local climate conditions.

Land-use: The modelling of the land-use system draws on the raster-based Agro-Ecological Zones land production planning model (AEZ) [431]. A resolution of approximately 250 meter time 250 meter was used to derive the production potential of the farmland used for ethanol production. Further, AEZ served to calculate irrigation requirements under different climate scenarios and fertiliser input required by various crops under different conditions like crop cycles per year.

Water: The water system was modelled using the Water Evaluation and Planning System (WEAP) [432] tool. WEAP is a tool for water resource planning, which was applied to assess the implications of local municipal and agricultural water requirements on national water supply schemes. Within WEAP, Mauritius' rivers were modelled as about 60 catchment areas. Each of them was characterised by specific hydrological and climatic profiles and land-cover classes, interlinked with its reservoirs and the five main aquifers of the island.

Further information about the linkages between WEAP and AEZ as well as background on the structure and set up of these models will be presented in a forthcoming publication [433].

Energy: The energy system was assessed with LEAP, which was set up to model the extraction and conversion of energy to meet demand. More detail on LEAP is provided in Section 5.4 of the introduction to the thesis.

2.2 'Current Practice Approach'

In the Current Practice approach, the LEAP tool was used to calculate:

- Average[167] power plant dispatching and future capacity requirements.

[167] The temporal information within LEAP is based on time slices. The accuracy of the dispatching modelled with LEAP therefore relates to the chosen number and definition of

- Ethanol production from sugar cane based on data regarding historic sugar cane harvests.
- Changes in fuel imports to the island due to the substitution of gasoline with ethanol.
- The effects of changes in rainfall patterns on generation.
- Greenhouse gas emissions, both on the island, as well as associated external emissions due to fuel processing and fertiliser supply to the island. This includes emissions associated with oil refining, coal processing and fertiliser production.

Note that in scenarios where sugar cane is used for ethanol instead of sugar production, external economic effects outside of Mauritius were not considered. Those could be significant, yet are difficult to assess. For example, the loss of area for sugar cane farming could be compensated by increases in farm land in other sugar producing countries. This could potentially lead to deforestation and associated greenhouse gas emissions.

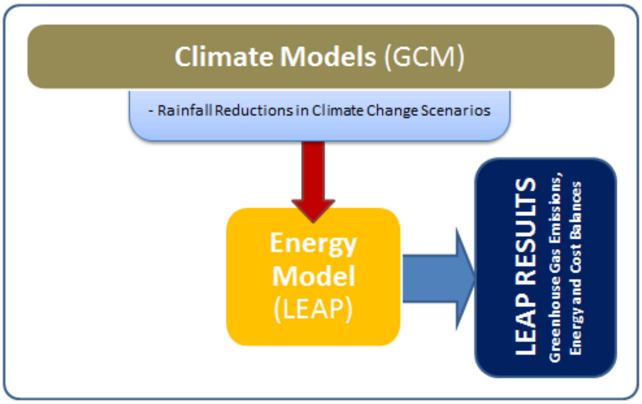

Fig. 34: Schematic of Current Practice approach

The energy system was set up based on historical demand data from the period 2005 to 2009 and generation data from 2005 to 2008 [426,428,434–439].

time slices as opposed to the detailed temporal resolution required for the daily dispatching by a system operator. Refer to Kannan [339] for a view on the value of increased temporal resolution.

Aligned with historical growth rates, an electricity demand growth of 3.5% was assumed. Any additional electricity requirements for pumping for irrigation and desalination were explicitly entered in the model. Economic considerations are based on an assumed oil price of 80 USD per barrel, a coal price of 60 USD per ton[168] and a sugar export price of 420 USD per ton.

At these prices the losses associated with reduced sugar exports are lower than the gains from the reduced imports of gasoline. Prices vary and are likely to be volatile in global markets. The positive cost-benefit balance is therefore not guaranteed. For an oil price of 100 USD per barrel and sugar prices higher than 700 USD per ton, ethanol production would not be profitable any longer [52]. Part C focuses on a comparison of differences in key energy dynamics with and without an integrated CLEWS approach. A detailed sensitivity analysis of the costs is outside of its scope

To model the electricity generation, all power plants and co-generating processing plants that export electricity to the national grid were modelled individually. Future power expansions plans were taken into account [406,440]. Any additional future capacity needs were assumed to be met by investments in coal-fired power plants to meet the base load and oil-fired power plants to meet balancing requirements[169]. Efficiencies and capacity factors of power plants were calibrated from historical data. Power plants were dispatched giving priority to those with the lowest short run marginal generating costs. Capital, operating and fuel costs were chosen according to data based on assessments of comparable international plants [306,441]. Annex G contains an overview of key power plant input data.

While hydropower generates less than 5% of the total electricity, it is strongly affected by the rainfall reductions in scenarios considering climate change. This is due to reduced inflows, potentially increased reservoir outflows and diversions to meet other water demands in times of shortage. A hydropower plant connected to a reservoir is assumed to be able to generate electricity in all months where the storage volume is more than an assumed 'dead storage' capacity of 5% of the total.

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168 Whenever ton is used as a unit in this thesis, it refers to metric tons.

169 Coal-fired power plants were assumed to contribute 70% of future capacity requirements for meeting peak demand. Oil-fired power plants were assumed to provide the remaining 30%, plus requirements to meet the system's reserve margin of 21%. For balancing requirements, the minimum share of oil based generation in the total mix was set to 15%. This compares to a national target to reduce the share of oil to 20% in 2025 [406].

A yearly 'hydro factor' was calculated. This factor de-rates the hydropower generation should the times with low storage volumes increase in the future. This could be due to the future impact of climate change or increases in reservoir outflows. Smaller hydropower plants which are not connected to reservoirs are assumed to reduce their generation by the same share that the average river flow is reduced. The monthly storage volumes and river flows were calculated by assuming river flow reductions to equal the expected rainfall reductions in per cent. No increases in competing water uses were considered in the 'Current Practice approach', e.g., for agricultural, municipal or industrial water demands.

2.3 'CLEWS Approach'

When reassessing the energy system considering the CLEWS approach, additional linkages between the energy model and the land-use and water model were taken into account. The required steps for this assessment were as follows:

1. Identify the interactions between the climate, land-use, energy and water resource systems. This first step can be considered as the most important step, and might require some form of collaboration with experts on the various resource systems.
2. Quantify these interactions. Such quantification focused, for example, on the groundwater demand for irrigation and the associated energy requirements for pumping.
3. Represent the interactions within the modelling framework.
4. Clearly define the required exchange of data between the resource models and its format. This is referred to as 'soft-linking' the individual models and is only required if separate modelling tools are applied.
5. Calibrate the modelling tool(s) based on historical data. Conveniently, this is first done through separated model runs, without considering any linkages between the models.
6. Develop scenarios to compare the implications of various key assumptions on future development pathways.
7. Represent the scenarios in the modelling tool(s).

8. As some outputs from one model might serve as input data for another, iterations may be required before a convergent solution emerges.
9. Interpret results and the differences between the Current Practice and the CLEWS approach.

Fig. 35 provides an overview of the interactions between these tools.

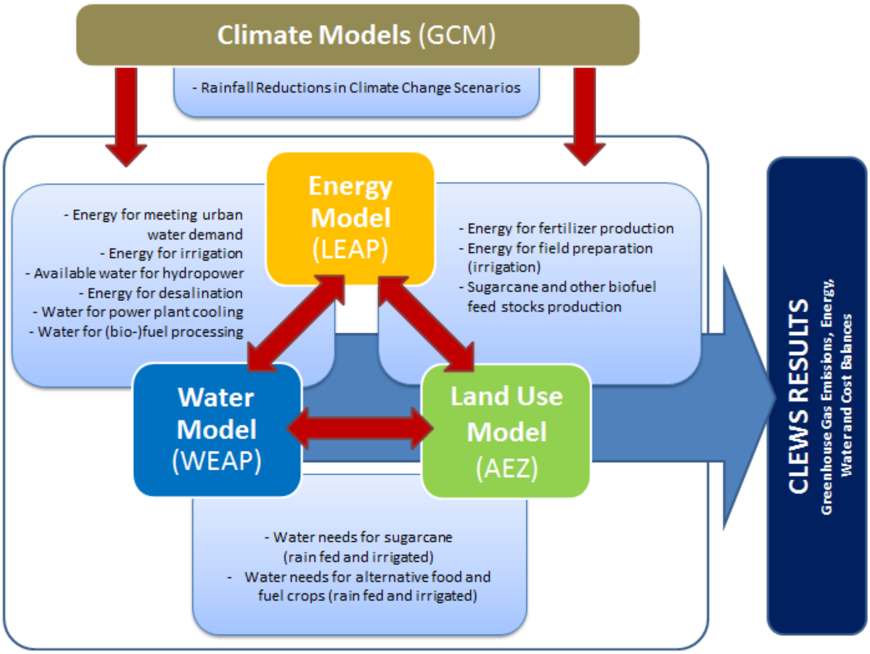

Fig. 35: Schematic of CLEWS approach

While an energy model on its own can be developed relatively straightforward based on data published in literature, pursuing the CLEWS approach comes with a considerable level of effort. Agreeing on a clear timeline, resolution and format of the inputs and outputs of the various modelling tools is therefore a necessity for a successful CLEWS assessment. Further, common assumptions and scenarios have to be well thought through and agreed on upfront. Any later change is a potential cause of errors if not implemented correctly in all models and scenarios, and might cause significant delays if not scheduled for.

The basic structure of the LEAP model was kept exactly the same as in the Current Practice approach. However, the following linkages to the other resource models were taken into account:

- The bioenergy production potential and fertiliser requirements for growing an alternative crop were derived from the land-use model.
- Additional[170] water pumping demands were incorporated as input values to the energy model. Those demands include pumping for urban water supply and sugarcane processing as derived from the water model, and pumping for agricultural irrigation as derived from the land-use model.
- Desalination demand for urban water supply was included as another input value to the energy model.
- Monthly storage volumes and river flows were derived from the water model. This enabled a consideration of competing water demands like agricultural or municipal demands. The hydropower generation was calculated based on these storage volumes and river flows following the same logic as in the Current Practice approach.
- Water demands for ethanol production and power plant cooling requirements were derived as output data from the energy model and fed into the water model.

More detail on the overall CLEWS approach and its application on Mauritius will be provided in a forthcoming publication by Hermann et al. [433]. This related effort presents further background on the applied climate, land-use and water models. It maps the interactions between the individual resources models and shows overall results including greenhouse gas emissions, water supply dynamics and crop productivities.

[170] Additional to the demand in the business as usual scenario of the Current Practice approach.

3 Scenarios

In line with the long-term energy strategy of Mauritius, the effects of increases in local ethanol production were investigated up until 2030. Ethanol was assumed to be added to the fuel mix of the local car fleet, or exported if deemed beneficial[171]. Changing weather patterns and decreasing rainfall are of concern to the Government of Mauritius as the island is prone to drought [443]. Therefore, the effects of climate change were considered.

In addition to a "business as usual" case based on historical trends and current government targets for renewable electricity generation, the scenarios to model these developments were grouped as follows:

- **Scenarios without Climate Change Considerations:** The sugar cane processing plants 'Medine' and 'F.U.E.L' are converted to produce ethanol instead of sugar from 2015 onwards.
- **Scenarios with Climate Change Considerations:** Additionally, the effects of climate change are simulated by decreasing rainfall linearly to 20.4% during the period from 2010 to 2030. This is based on a worst case scenario derived from the selected General Circulation Models [430,431].

The following section outlines the scenarios established based on these considerations. If possible, the exact same scenarios were set up for both, the Current Practice and the CLEWS approach. However, one scenario explicitly relies on an integration of resource systems (2NC+CC^{CLEWS}). It was therefore only possible to assess this scenario pursuing the CLEWS approach.

Table 15 provides an overview of all of the scenarios assessed and their abbreviations. Note that the superscript '^{CLEWS}' refers to the assessment of a scenario based on the CLEWS approach. Scenarios without this superscript

171 This may occur if the car fleet is not able to absorb all of the ethanol produced. In this case, it was assumed that there is an external market for ethanol from Mauritius and that import prices of gasoline per energy content equal export prices for ethanol. Therefore, it has no economic implications if the ethanol is consumed on Mauritius or exported. Amigun and von Blottnitz [442] report that such exports are already taking place, with an ethanol producer aiming at increasing its exports to 30 million litres per year.

were assessed based on the Current Practice approach. The extension '+CC' refers to scenarios considering climate change.

3.1 Current Practice Approach

3.1.1 Scenarios without Climate Change Considerations

3.1.1.1 BAU: Business as Usual

In this scenario, electricity and gasoline demand growth follow historical trends. Electricity and heat generation from bagasse continues at current levels, but no ethanol is produced. Future renewable electricity generation shares reflect the targets outlined in the long-term energy strategy of Mauritius. Rainfall patterns, reservoir levels and thus hydropower availability were expected to reflect historical levels. The results of the following scenarios assessed with the Current Practice approach are illustrated as changes to this baseline scenario.

3.1.1.2 1GEN: Ethanol – First Generation

Sugar production is changed to so-called 'first generation' ethanol production[172]. Ethanol is blended with gasoline to meet domestic transportation fuel demand or used for export. The by-product bagasse is used to produce electricity at the sugar cane processing plants. Excess electricity is sold to the national grid.

3.1.1.3 2GEN: Ethanol – Second Generation

Sugar cane is again used to produce ethanol. However, excess bagasse is no longer used to produce electricity for the national grid. Instead, it is also converted to ethanol via hydrolysis, using so-called 'second generation' technologies[173].

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172 'First generation' refers to ethanol production from sugar and starch crops [444].

173 'Second generation' refers to ethanol production from lignocellulosic biomass. This extends the potential feed stock sources, e.g., to bagasse from sugar cane, waste products from agriculture and forestry, or municipal waste [444].

3.1.2 Scenarios with Climate Change Considerations

3.1.2.1 BAU+CC: Business as Usual, Water Stress

This scenario builds on the business as usual (BAU) scenario, but with rainfall reductions due to climate change. No ethanol is produced.

3.1.2.2 1GEN+CC: Ethanol – First Generation, Water Stress

This scenario builds on the first generation ethanol production scenario (1GEN), but considers rainfall reductions due to climate change[174].

Table 15: Overview of Abbreviations for all Scenarios

	Business as usual	Ethanol – First generation	Ethanol – Second generation
Current Practice approach	BAU BAU+CC	1GEN 1GEN+CC	2GEN -
CLEWS approach	BAU^{CLEWS} BAU+CC^{CLEWS}	1GEN^{CLEWS} 1GEN+CC^{CLEWS}	2GEN^{CLEWS} 2NC+CC^{CLEWS}

3.2 CLEWS Approach

All scenarios assessed with the Current Practice approach were reassessed with the CLEWS approach, i.e., taking the linkages with the water and land-use models into account. The results are presented as changes to the respective baseline scenario (BAU^{CLEWS}). Further, an additional scenario was investigated, which could not have been assessed pursuing the Current Practice approach:

174 The second generation scenario (2GEN) was not reassessed taking climate change into consideration. This is because results showed that the first generation scenario (1GEN) is economically more attractive. This would not change when considering climate change.

3.2.1 2NC+CC^{CLEWS}: Ethanol – Second Generation, New Crop, Water Stress, CLEWS Approach

This scenario builds on the second generation ethanol production scenario (2GEN^{CLEWS}). It explores the potential of growing an alternative crop as ethanol feedstock for processing at the two selected processing plants. The characteristics of this alternative crop were aligned with those of corn. It allows for two harvest cycles and is more drought resistant than sugar cane. All other processing plants continue to rely on sugar cane for sugar production. As for all climate change scenarios, rainfall is reduced based on the outlined climate change assumptions.

3.3 Assumptions Related to Agriculture and Water Supply

If not stated otherwise, sugar cane production is maintained at historical levels in all scenarios[175]. When applying the CLEWS approach, the water supply and land-use models were set up accordingly to support this level of production: When precipitation is insufficient, irrigation is used to meet any additional water requirements for feed stock. The irrigation water demand is covered by surface runoff. Should this not suffice, groundwater pumping is considered. Urban water demand is met through rivers and reservoirs, groundwater pumping or with supplementary desalination[176]. Desalination is considered for meeting urban demand if additional pumping would reduce the available groundwater by more than 15% below the historical minimum. Groundwater is already currently at risk of saline intrusions. Therefore, this appears as a rather conservative assumption with regard to demand increases for desalination.

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175 The scenario 2NC+CC^{CLEWS} explicitly considers the introduction of a new crop instead of growing sugar cane at Medine and F.U.E.L.

176 Recall that hotels are already obliged to provide provisions for desalination plants since 2005 [423].

4 Results

Based on the outlined methodology, this section presents the results for the business as usual, and the first and the second generation scenarios. Each of them is first assessed applying the Current Practice approach with and without climate change considerations, followed by a reassessment pursuing the CLEWS approach. Changes in the results between different scenarios and the business as usual case are presented for the year 2030. This serves to assess what level of detail is gained and to what extent the derived potential conclusions vary when considering the more integrated CLEWS approach.

4.1 Business as Usual

4.1.1 Current Practice Approach

Based on the calibration with historical values and future expansion plans, Fig. 36 shows the generation mix over the modelling period (**BAU**). Electricity generation increases from 2,240 GWh in 2005 to 5,260 GWh in 2030. Most future demand is met by coal-fired power plants (grey areas), with a significant reduction of the share of oil-fired power generation (red areas). This shift from petroleum products to coal is in line with the government's energy strategy. Reducing the dependence on oil serves to minimise the associated higher geopolitical risks and avoid the more volatile prices.

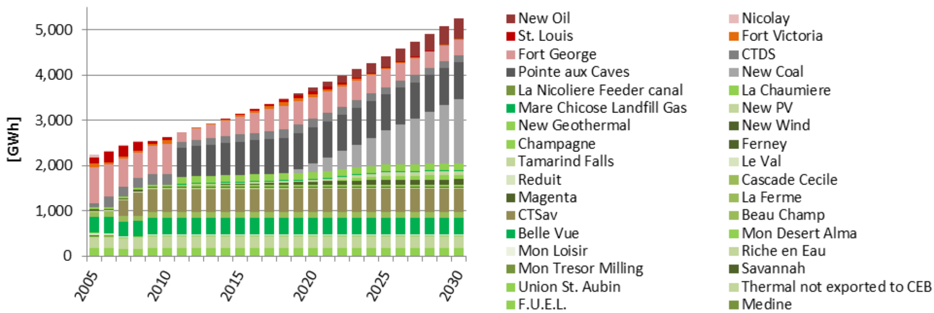

Fig. 36: Generation mix by power plant for the business as usual (BAU)

Red areas are assigned to power plants which are fired with petroleum products, grey areas to coal-fired power plants and green areas to renewable energy, including plants running on both bagasse and coal. This colour coding is maintained throughout Part C.

The BAU scenario was reassessed taking the effects of climate change into account (**BAU+CC**). Its impact was found to be insignificant when looking at overall generation levels. However, this changes when focusing specifically on hydropower: reductions of 40% from 97,500 MWh to 58,900 MWh occur in 2030 (BAU vs. BAU+CC). These reductions are mainly compensated through increases in coal, followed by oil-fired power plants. This results in an increase of greenhouse gas emissions by 42,000 tons of $CO_{2\text{-eq}}$ in 2030 compared to the BAU. This increase constitutes just over one per cent of Mauritius' total net emissions [421].

4.1.2 CLEWS Approach

The dynamics of the BAU scenario without climate change remain very similar once reassessed with the holistic CLEWS approach (**BAU$^{\text{CLEWS}}$**). There are only some minor changes in hydropower generation towards the end of the modelling period due to increases in urban consumption. However, when reassessing the BAU taking climate change into consideration (**BAU+CC$^{\text{CLEWS}}$**), several dynamics would have been overlooked: through the CLEWS approach an additional electricity demand for water supply is identified, which amounts to 67,000 MWh in 2030. This is due to sea water desalination and pumping to meet urban water demand and as well groundwater pumping for irrigation (left graph of Fig. 37).

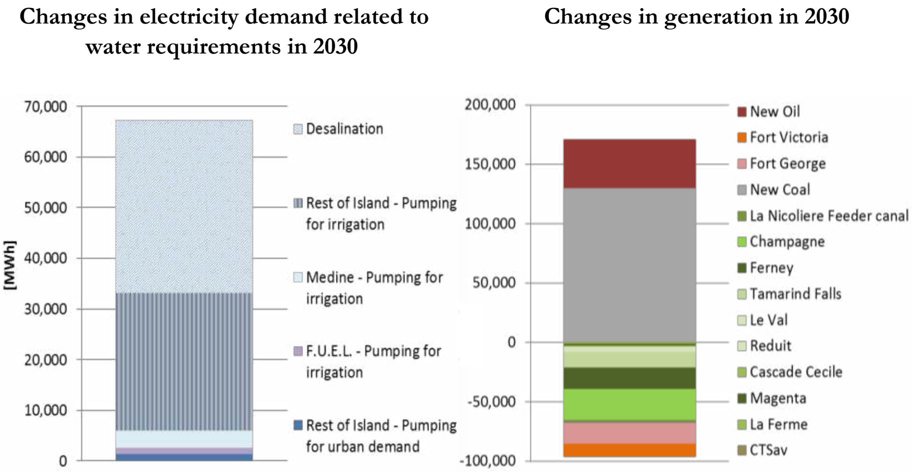

Fig. 37: Changes in electricity demand and generation for BAU+CC$^{\text{CLEWS}}$ compared to BAU$^{\text{CLEWS}}$

Further, due to the consideration of climate change, the hydropower generation is reduced from 83,200 MWh to 16,200 MWh in 2030 (BAU^{CLEWS} vs. $BAU+CC^{CLEWS}$). This 81% reduction is much more significant than the 40% reduction as observed in the corresponding scenarios of the Current Practice approach (BAU vs. BAU+CC). The Current Practice approach would therefore lead to an over 260% higher hydropower generation in 2030. This may not considerably affect the total electricity generation given the limited role of hydropower for Mauritius. However, for countries with higher hydropower shares such dynamics should not be overlooked.

Fig. 38 depicts the reasons for this overestimation. As identified by the water model, withdrawals from reservoirs for urban and agricultural water demand increase when considering climate change. This accelerates the drawdown of the reservoirs, leaving little water to be used for hydropower generation (graph on the left of Fig. 38). Without the CLEWS approach, these increasing withdrawals were overlooked and all reservoirs are able to recover once they have been emptied in summer, as shown on the right of Fig. 38.

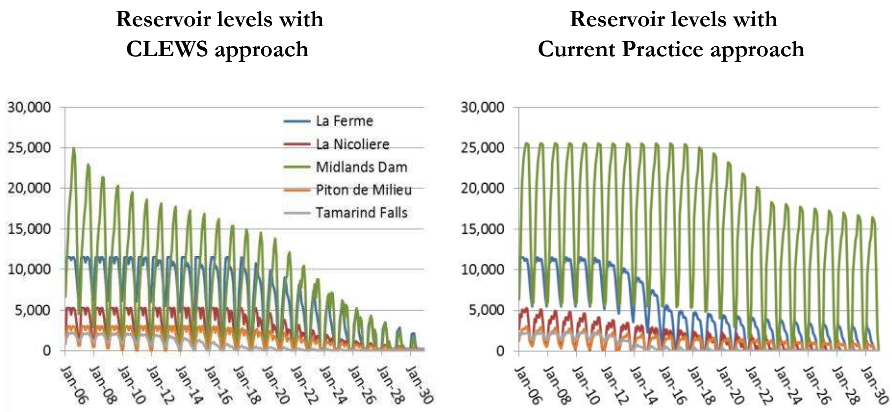

Fig. 38: Projected reservoir levels in thousand m³

The additional demand and lower hydropower generation when considering climate change result in changes in generation as illustrated for 2030 in the graph on the right of Fig. 37. The bars with negative y-axis values show power plants which decrease their generation in the $BAU+CC^{CLEWS}$ scenario compared to the corresponding business as usual scenario (BAU^{CLEWS}). Similarly, the bars with positive y-axis values represent power plants which are expected to increase their output: these are oil and coal-fired power plants, which leads to an increase in greenhouse gas emissions of 154,000 tons of $CO_{2\text{-eq}}$ compared to the corresponding business as usual case without climate change.

4.2 Ethanol – First Generation

4.2.1 Current Practice Approach

In this scenario it was assumed that the sugar cane processing plants Medine and F.U.E.L. is converted to produce first generation ethanol from sugar cane (**1GEN**). The ethanol would be used to replace some of the gasoline required for the car fleet. 1,950 TJ of ethanol per year could be produced by the two plants. This could be used to reduce gasoline imports or for export. It compares to a total demand for gasoline of 5,350 TJ in 2010 [408]. Due to the higher electricity requirements for producing ethanol as compared to sugar, the two sugar cane processing plants would export 3,400 MWh less electricity to the national grid. This would be compensated by increased generation from coal and oil-fired power plants, as illustrated for 2030 in the left graph of Fig. 39.

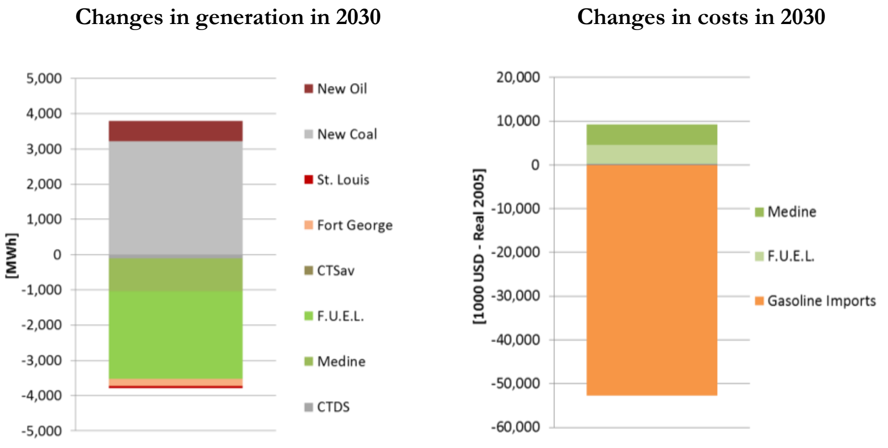

Fig. 39: Changes in selected energy dynamics for 1GEN compared to BAU

However, the resulting greenhouse gas balance is very much in favour of the ethanol production. 148,000 tons of $CO_{2\text{-eq}}$ could be avoided in 2030. This is due to the use of ethanol as a substitute for gasoline in the transport sector and the reduced external emissions of associated oil refining. Also from an economic perspective, when focusing solely on the energy system, this measure would be very favourable. The reduced gasoline imports outweigh the cost increases for the ethanol production at Medine and F.U.E.L. by far, as shown on the right of Fig. 39. The total net benefit of 43.5 million USD in 2030 is derived by subtracting the benefit due to the reduced imports from the additional costs at Medine and F.U.E.L.

Next, the first generation scenario is reassessed taking climate change into consideration (**1GEN+CC**). The corresponding changes in generation are due to reductions in hydropower (as observed in BAU+CC). This is compensated by additional generation from coal and oil-fired power plants. The ethanol production of 1,950 TJ remains the same as in the 1GEN scenario. Greenhouse gas reductions of 106,000 tons of $CO_{2\text{-eq}}$ occur in 2030. Given the lower hydropower generation, these reductions are less significant than in the case without climate change (1GEN). From an economic perspective, the dynamics do not change significantly due to climate change (i.e., compared with the right graph of Fig. 39). The additional costs for coal and oil imports to compensate the reduced hydropower generation are negligible compared to the other cost factors. Ethanol generation therefore remains attractive.

4.2.2 CLEWS Approach

Next, first generation ethanol production is reassessed with the CLEWS approach. Without taking climate change into account (**1GEN$^{\mathbf{CLEWS}}$**), very little interaction with the actual land-use or water system occurs.

However, from an economic perspective, there is an important linkage with the agricultural sector: the use of sugar cane for ethanol production reduces the income from sugar exports by 48.0 million USD. Some of this is compensated by the reduced expenses for sugar production of 20.6 million USD (Fig. 40). Thus, the total economic benefit of ethanol production is significantly reduced by 27.4 million USD[177]. This type of economic links to another sector might be simple in this case. However, it can easily become more complex if several feedstocks compete for various uses like electricity generation, biofuel production or food processing.

[177] However, the benefits of increasing Mauritius' energy security by reducing its import dependence on gasoline remain.

Fig. 40: Changes in costs for $1GEN^{CLEWS}$ and $2GEN^{CLEWS}$, both compared to BAU^{CLEWS}

When adding climate change considerations (**$1GEN+CC^{CLEWS}$**), the additional water demand for producing first generation ethanol from sugar cane has an insignificant impact on the additional energy demand. The related dynamics presented in the right graph of Fig. 37 therefore remain. From an economic point of view, the overall changes in costs remain similar to those of the corresponding CLEWS scenario without climate change ($1GEN^{CLEWS}$) as shown in the left graph of Fig. 40. However, additional costs of 8.2 million USD are incurred to compensate for the reduced hydropower generation. There are no greenhouse gas emission reductions relative to the BAU^{CLEWS} any longer. Rather, an increase of 10,000 tons of $CO_{2\text{-eq}}$ occurs. This is due to the lower hydropower generation and the higher total electricity demand, which is met by coal and oil-fired power plants.

4.3 Ethanol – Second Generation

4.3.1 Current Practice Approach

If the excess bagasse is also converted to ethanol (**2GEN**), both processing plants are no longer able to export any electricity to the grid. Instead the ethanol plants have to buy electricity from the grid, resulting in a higher total electricity demand. Therefore, as illustrated by the graph on the left of Fig. 41, the increases in generation by coal and oil-fired power plants outweigh the decreases in generation at Medine and F.U.E.L. The overall ethanol production increases to 2,660 GJ at the price of slightly higher overall costs compared to the first generation scenario (1GEN): while costs for gasoline imports decrease, this is outweighed by the higher costs of producing second generation ethanol (graph on the right of Fig. 41, compared with graph on the right of Fig. 39).

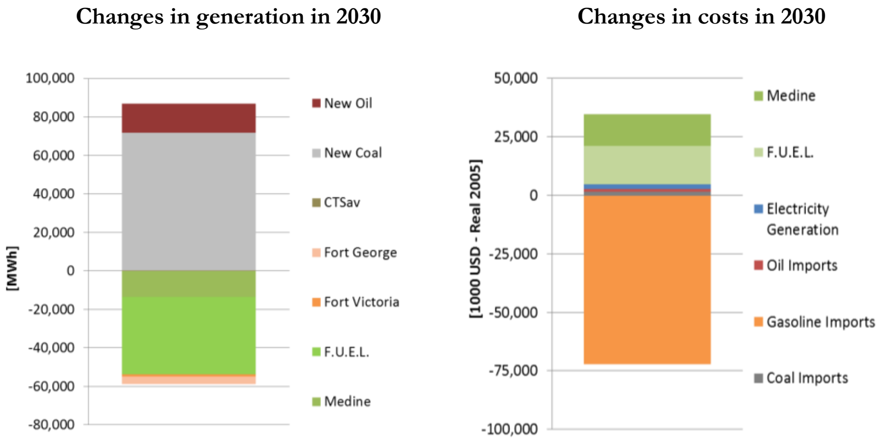

Fig. 41: Changes in selected energy dynamics for 2GEN compared to BAU

The economic benefit of producing second generation ethanol amounts to 37.2 million USD in 2030, and is therefore significantly lower than for first generation ethanol production. The greenhouse gas reductions of 123,000 tons of $CO_{2\text{-eq}}$ in 2030 are as well lower than in the first generation scenario. Overall, apart from the opportunity to increase Mauritius' energy security by reducing its import dependency on gasoline (or to diversify export earnings through additional ethanol exports), the first generation scenario therefore seems favourable. When pursuing the Current Practice approach, taking climate change into consideration would only affect the hydropower generation, but not the profitability of the ethanol generation. Second generation ethanol production would therefore remain less attractive.

4.3.2 CLEWS Approach

As in the 1GEN^{CLEWS} scenario, very little interaction with the actual land-use or water system occurs in the 2GEN^{CLEWS} scenario. However, income from sugar exports and the expenditures for sugar production are reduced (left graph of Fig. 40). Thus, as in 1GEN^{CLEWS}, the total economic benefit of ethanol production is significantly reduced by 27.4 million USD when pursuing the CLEWS approach.

When considering climate change, applying the CLEWS approach does not change the fact that second generation ethanol production would remain less attractive then first generation ethanol production. The CLEWS approach was therefore applied in order to investigate the profitability of growing an alternative crop[178] as ethanol feedstock for the processing plants Medine and F.U.E.L. (2NC+CC^{CLEWS}).

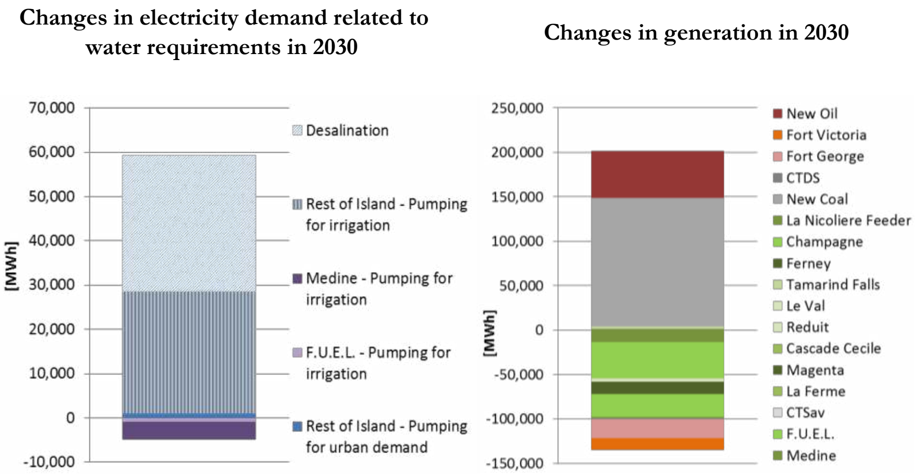

Fig. 42: Changes in electricity demand and generation for 2NC+CC^{CLEWS} compared to BAU^{CLEWS}

Despite its two crop cycles and even as climate change is considered, the alternative crop has a lower overall energy yield and requires less electricity for pumping and irrigation than sugar cane does without taking climate change into account. The electricity demand at the two selected processing plants is therefore lower than in the business as usual case without climate change

178 Its characteristics were aligned with those of corn.

(negative bars in graph on the left of Fig. 42). This reduced water demand also translates into a lower demand for desalination compared to the other climate change scenarios (compare to right graph of Fig. 37). As sugar cane is abandoned at Medine and F.U.E.L., no bagasse is available for electricity generation and both processing plants need to buy electricity from the grid. This additional electricity demand is met by coal and oil-fired power generation. The overall changes in generation when introducing a new crop and considering climate change are shown in the right graph of Fig. 42.

Despite the higher energy intensity of the new crop, due to the overall lower yield only 1,930 TJ of ethanol can be produced. This is almost the same yield as with first generation ethanol from sugar cane. Also the overall economic balance is less favourable than for first generation ethanol production with sugar cane. This is due to the higher processing costs associated with second generation ethanol production, the higher electricity generation requirements and the lower ethanol production. Further, greenhouse gas emissions increase to 59,000 additional tons of $CO_{2\text{-eq}}$ as compared to the business as usual case (BAU^{CLEWS}). Overall, while diversifying agriculture is one of the priorities of the Government of Mauritius, the new crop performs worse than sugar cane from a cost and climate change perspective.

4.4 Adding Value with CLEWS – Summary of the Findings

When assessing the energy system based on the Current Practice approach, first generation ethanol production seems very advantageous for Mauritius. It is characterised by a positive economic balance of 43.5 million USD, increased energy security through the production of 1,950 TJ ethanol and 148,000 tons of $CO_{2\text{-eq}}$ reductions in 2030. Second generation ethanol production appears less attractive. Apart from the increases in ethanol production, both the cost and greenhouse gas balances look worse.

The conclusions regarding first generation ethanol production do not change significantly when considering climate change. While hydropower generation decreases by 40%, this still constitutes an insignificant fraction of the overall electricity generation. The energy security situation compared to the business as usual deteriorates slightly. Additional coal and oil net imports total 400 TJ. The overall greenhouse gas emission reductions now amount to 106,000 tons of $CO_{2\text{-eq}}$.

When pursuing an integrated CLEWS approach, the picture changes considerably. The economic balance for both first and second generation ethanol production decreases by around 27.5 million USD. This corresponds to over 60% of the total net benefit for first generation and over 70% for second generation ethanol production. The reductions are mainly due to the losses in sugar exports. Greenhouse gas reductions and ethanol production remain basically the same as in the Current Practice assessment.

When assessing the climate change scenarios, the added value of the CLEWS approach becomes even more evident. These scenarios are characterised by an additional electricity demand for water supply of 67,000 MWh. The hydropower generation decreases more significantly and, in 2030, constitutes only 28% of the generation derived from the Current Practice assessment. Further, compared to the Current Practice approach, the additional net imports of oil and coal increase 3.5-fold to 1,380 TJ in the first generation ethanol scenario[179]. This ultimately results in an increase of greenhouse gas emissions by 10,000 tons of $CO_{2\text{-eq}}$ instead of the previous decrease. Finally, there is a whole new scenario which could not have been assessed without the CLEWS approach. This scenario focuses on the introduction of a new crop with its characteristic fertiliser, water and consequent energy demands as well as greenhouse gas emissions[180].

5 Conclusions

Based on both the present discussion and related analysis [64], a basic level of collaboration with professionals from outside of the energy sector appears valuable when setting up an energy assessment. Such collaboration helps to indicate upfront if any future resource related stresses might occur. In some cases it may become apparent that a deep integration among CLEWS is not

[179] This refers to *additional imports* compared to the respective business as usual cases (BAU and BAU^{CLEWS}). While such a comparison is commonly used for energy models, a comparison of the total values instead of the additions would obviously yield much lower differences in per cent.

[180] The crop in this scenario did not perform better than sugar cane. However, it requires a CLEWS assessment to come to this conclusion and to justify the assumption that sugar cane is also preferable once climate change considerations are taken into account.

required. In other instances its added value might justify the modelling and coordination effort involved.

In the present study, a policy for agricultural diversification, the existence of ethanol production targets, and the potential need for desalination suggested upfront that interdependencies between resource systems may need to be accounted for in the energy model. The subsequent analysis showed that moving from water surplus to water stress increased the level of CLEWS interactions to a point where national dynamics around an ethanol production policy changed significantly.

In general, a CLEWS approach is likely to be valuable for countries intending to implement integrated policies with potential implications for multiple resource systems. High shares of hydropower and expected climate-induced rainfall changes might also indicate the relevance of a CLEWS assessment. In addition to climate change, conflicting water management priorities may impede the future availability of water for electricity generation. Applying a CLEWS approach may further enable a more holistic assessment of greenhouse gas emissions. This could serve, for example, to assess the climate implications of ensuring energy and water supply while considering technological advances and changes in agricultural practices.

The additional commitment of interlinking the energy model with external climate, land-use and water models involves a non-trivial effort. However, the purpose of an energy model should be to depict a potential future as adequately as possible in order to help derive strategies that are consistent across sectors. The underlying research work has shown the importance of capturing linkages between CLEWS for informing such consistent strategies. In response to this work, the Government of Mauritius has announced the appointment of a high-level CLEWS panel. This panel will ensure an integrated approach to CLEWS-related policies is adopted [65].

Concluding Remarks and Recommendations

Section 1 presents overall conclusions. It briefly summarises those presented in the last chapters of Section 1 and 2 of Part A, and in the last sections of Part B and Part C of this thesis. Section 2 identifies selected areas for future work.

1 Concluding Remarks

Improving integration within and between models can enable more holistic assessments of policy, operational and investment strategies as well as their interrelations with our economies and the wider environment. However, the uncertainties and time requirements involved, demand choosing an appropriate level of integration. Since inflated models may be computationally intensive and opaque, this increased integration should only be considered if it is expected to significantly impact the derived findings. That decision may often be up to the analysts, relying on their experience, institutional settings and coordination with experts from other fields. It is the hope of the author that this thesis may provide related insights by demonstrating how results changed when increasing the level of integration considered in models.

Smart Grids are expected to facilitate an improved integration between the supply and demand of electricity. The integration of Smart Grid and traditional supply options is limited in many long-term modelling efforts. In part this is because the modelling toolkits available to the analyst are still evolving. Accordingly, the open source model OSeMOSYS was enhanced in this thesis. This model provided a relatively transparent test bed to demonstrate potential contributions of Smart Grids to reduce peak load requirements, as assessed in a simple case study. In addition to the modelling, a set of Smart Grid options for developing countries was presented and quantitatively assessed in this thesis.

The efficiency improvements and the more user centric approach they may facilitate might ultimately help to accelerate electrification rates in sub-Saharan Africa. Expanding access will also require significant expansions of the limited existing electricity infrastructure. An upfront adoption of some of these Smart Grid options may be economically more efficient than a later transition to more intelligent grids by replacing and upgrading existing infrastructure. This may provide an advantage which is largely unique to developing countries.

In instances where power system flexibility needs to be considered, models with a long-term outlook may need to consider integration between timeframes. The need to bridge the gap between operational power system models with high temporal detail and the comparatively rather coarse long-term energy models has been showcased using Ireland as a case study. This case study demonstrated that integrating operational constraints in long-term models improved the mismatch in dispatch results from 21.4% to 5.0%. This mismatch was measured in comparison to a short-term model with more technical detail and an over 700 times higher temporal resolution. Further, up to 23.5% of the capacity investments differed when omitting operational constraints. Considering such short-term constraints is therefore essential when assessing long-term investment strategies, especially as ambitious international and national policies push for increasing shares of variable renewable energy sources. In addition to the gap between models, a potential gap between the requirement for flexible technologies and investment incentives was noted.

Finally, the importance of capturing the linkages between energy and other resource systems was demonstrated on a case study of the small island developing state of Mauritius. The analysis has shown that resource integration is especially important when considering integrated policies, climate change, limited resource availabilities and diverging resource management priorities. The relevance of this approach is however not limited to country assessments. From a local to a global level, whenever resources are limited, considering linkages between other resource systems might unveil some otherwise hidden opportunities for efficiency gains. Identifying such efficiency gains will help to avoid uncoordinated and potentially conflicting policies and accelerate the expansion of equitable access to these resources. This may help to deliver on local as well as international targets such as the MDGs or the energy goals underpinning the UN's Sustainable Energy for All initiative.

The modelling adaptations presented in this thesis provide a toolkit that might be used to gain insights into aspects of system integration. Some energy models may be more compatible with such adaptations than others. However the described model improvements are not an attempt to replace existing tools and were all explained in a generic way. This route was followed to help enable their implementation, at least to some degree, independently of any specific modelling tool. Further, many specialised models exist which are much better suited for detailed assessments of specific goals or subsets of the energy system.

While various dimensions of integration were considered in this thesis, the term is so vast that only a selection of possible topics was addressed – and important elements had to be excluded. However limited it is, I hope that the contribution made in this thesis will prove valuable and provide an addition to the important field of energy system analysis.

2 Recommendations for Future Work

This thesis investigated a small number of issues related to the treatment of systems integration in long-term energy models. There are clear opportunities to extend the analysis.

For example, a modelling tool was extended during the course of this thesis to consider a better integration between multiple regions [310]. However, apart from test model runs, no multi-regional assessments were performed. Further, no direct integration between energy and climate models was taken into account. Energy system emissions were however calculated in both Part B and Part C of this thesis and results from climate models were used as inputs for the resource models applied in Part C. Integration with other economic sectors by linking bottom-up with top-down models was also not performed as part of this thesis. Yet, this thesis was able to consider elements within each of the categories of integration as listed in Section 2 of the introduction.

In addition to expanding the considered level of integration, future work may also focus on extending the applications of the modelling approaches presented in this thesis. For example, the CLEWS approach may be applied to other countries or regions to better identify resource linkages as well as key aspects which enable an upfront indication of the relevance of this approach for specific applications. Further, system-wide economic implications of increased investments in combinations of variable renewable energy sources may be assessed taking into consideration their geographical dispersion. Future modelling work may help derive insights on how best to accommodate increasing shares of renewable energy, such as through improved ramping characteristics of individual technologies, increased accuracy of wind forecasts, expanded storage capacities or through demand response measures facilitated by Smart Grids.

Further, energy security related questions regarding market integration might be assessed. For example, models could be extended to investigate the value of cross-border trade of electricity and operating reserves. Additionally, the links between electricity, heat and transportation demands might be analysed. This may help to assess what suites of technology investments would most effectively meet the demands placed on future energy systems.

These areas of future research are just a selection of possible extensions and applications of the work presented in this thesis. Various aspects of these areas have already been assessed in the literature, yet their combined consideration in an integrated modelling framework offers numerous opportunities for future insights. Further, various additional topics may profit from increased integration to ultimately help support the design of cohesive policy frameworks. Considering integration in the models informing such frameworks will hopefully point to synergies and help avoid inadvertently conflicting information by different modelling tools.

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Annex A SELECTED TOP-DOWN MODELS

Annex A.1 Input-Output Models

The term input-output analysis was coined by Wassily Leontief in the late 1930s [445]. This type of analysis builds on a set of linear equations to assess the interdependencies between the various sectors within an economy [445]. The interrelations between various goods are commonly summarised in input-output tables where commodities consumed by a sector and sectors consuming commodities are listed. The flows of commodities are commonly measured in monetary units, but physical units may as well be used [446]. Drawing these tables is commonly the task of national governmental institutions. The level of detail provided in such tables can be significant. For example, the U.S. input-output table for 2002 contains 56,760 lines of data to describe the use of commodities by industries [447]. Due to the effort involved in deriving these tables, they are not updated on a yearly basis and usually published many years after the data collection.

Input-output tables may be used to calculate 'output multipliers' for each sector. These multipliers can be applied to derive the required contribution of each commodity in all sectors to support an output increase of one financial unit within a single sector. As all direct and indirect effects across an economy are taken into account, insights can be gained regarding the extent to which sectors are linked with other parts of an economy. Increasing the demand for the output of a highly interlinked sector will positively affect demands across the economy and may therefore be a valuable target for supportive public investments. For the purpose of an analysis of the energy system, energy intensities of sectors may be combined with input-output tables. This enables exploring the implications of changes in sectoral activity on energy demand.

Input-output tables provide a snapshot of an economy. As such, changes within the interdependencies of the sectors cannot be captured without further modification of such tables. Further, they are based on the average consumption and production of a sector within a given year. Assessments of the response of a sector's production to electricity price signals are therefore beyond the scope of a simple input-output analysis and require more sophistication. For example, Campana et al. [23] fed output multipliers into an optimisation model to investigate energy efficiency measures and their effects on job creation.

Annex A.2 Computable General Equilibrium Models

A general equilibrium occurs when prices have adjusted so that demand equals supply of all commodities in the whole economy [448]. Computable general equilibrium models ensure that such an economy-wide equilibrium occurs. They may build on input-output tables to assess how structural changes disseminate through the economy [449].

CGE models use production functions based on elasticities to specify the output as a function of its combination of inputs such as material, labour, capital and energy [450]. For example, a higher energy price may negatively impact the production of energy intensive industries. Elasticities describe how a percentage change of one variable translates into a percentage change of another variable. They may be defined by considering production isoquants. In economics, an isoquant describes minimum combinations of inputs which all produce the same output [451]. It can be interpreted as a set of opportunities for meeting a given demand. For example, a specific heating demand may be met by an electric heating system or by additionally investing in insulation materials and thus reducing the electricity bill. The electricity price will then help decide which option is preferable. Isoquants may change over time due to learning by doing, technical progress and economies of scale [452].

Based on its reliance on production functions, CGE models enable a more dynamic assessment of policy measures than input-output models. A possible application could be to assess the implications of a CO_2 tax on employment or economic growth. Also, while economic sectors are commonly modelled at an aggregated level, CGE models may be interlinked with bottom-up models. Individual sectors may be singled out and technological detail added. For example, Laitner and Hanson [450] assessed investments in energy efficiency drawing on the AMIGA (All Modular Industry Growth Assessment) modelling system.

Annex B QUALITATIVE RANKING OF SMART GRID OPTIONS

This annex provides explanatory remarks regarding the qualitative ranking. The meaning of each ranking category is briefly commented on for each assessment criteria.

1. Consumers

++	Overall benefit for consumers with strong pro-poor characteristics
+	Overall benefit for consumers
o	Only minor or no impact on consumers
-	Some reduction in quality of service
--	Consumers are burdened by this measure

2. Operation & Quality of Supply

++	Significantly positive impact
+	Positive impact
o	Only minor or no impact
-	Negative impact
--	Significantly negative impact

3. Generation

++	Significant reduction of peak demand and/or reduction in losses
+	Reduction of peak demand and/or reduction in losses
o	Only minor or no impact on peak demand and/or reduction in losses
-	Increases in peak demand and/or losses
--	Significant increase in peak demand and/or losses

4. Environment[181]

++	Significant positive impact through efficiency increases or fuel substitution
+	Positive impact through efficiency increases or fuel substitution
o	Only minor or no impact
-	Negative impact

[181] The actual degree of this impact will depend on the generation mix.

-- Significant negative impact

5. Technical Complexity

++ Little technology requirements, or technologies which have already been successfully introduced in sub-Saharan Africa
+ Well known technologies, or existing experience in sub-Saharan Africa with comparable technologies; do not necessarily require system-wide integration
o Existing experience, but system-wide integration required
- Complex technologies; do not necessarily require system-wide integration, e.g., only at transmission grid or distribution level like smart meter installations
-- More complex technologies, usually requiring system-wide adjustments, e.g., smart meter installations together with smart appliances

6. Investments

++ Very small investments, or investments which can easily be refinanced
+ Well confined, targeted smaller investments allow testing out the business case
o Type of investment strongly dependent on applied design and system integration
- Investments whose profitability cannot easily be tested out beforehand, e.g., because they are system-wide like smart meter installations
-- Overall larger investments, usually for infrastructure, or large investment requirements from a consumer perspective, e.g., for smart appliances

7. Human Capacities

++ Already common practice in sub-Saharan Africa
+ Capacities are to a large extent available within country
o Capacities can easily be built, e.g., because they are only required centrally at utility level
- Significant in-country capacity requirements for implementation or operation

-- Significant in-country capacity requirements for both implementation and operation

8. Policy, Regulation & Standards

++ Already existing and well established supportive policies and regulation
+ Already in preparation or no or only little requirements
o supporting frameworks required, but extensive existing and easily translatable precedence
- Some policy support, regulation or technical standards required
-- Strong dependence on policy support for effectively implementation

9. Applicability of Models for Pre-assessments

++ Existing case studies and precedence in literature
+ Existing electrification model adaptations and runs
o Current electrification models need to be extended
- Further studies, e.g., on consumer acceptance, required as input to extended electrification models
-- Impacts are difficult to model

Annex C MODELLING ELEMENTS OF SMART GRIDS – CODE IMPLEMENTATION

The full model code is given below. The code below can effectively be cut and pasted into a GNU MathProg model file and run. The reader is referred to www.osemosys.org for more information and a non-pdf version of the code, as well as sample application files. Note that the '#' symbol precedes a line of code not used in the model and is included for comments.

Annex C.1 Variability in Electricity Generation

```
# Model Definition #

# SETS #

set YEAR;
set TECHNOLOGY;
set TIMESLICE;
set FUEL;
set EMISSION;
set MODE_OF_OPERATION;
set REGION;

# PARAMETERS #

# Global #

param YearSplit{y in YEAR,l in TIMESLICE};
param DiscountRate{t in TECHNOLOGY, r in REGION};

# Demand #

param SpecifiedAnnualDemand{y in YEAR,f in FUEL, r in REGION};
param SpecifiedDemandProfile{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION};
param AccumulatedAnnualDemand{y in YEAR, f in FUEL, r in REGION};

# Performance #

param CapacityToActivityUnit{t in TECHNOLOGY, r in REGION};
param TechWithCapacityNeededToMeetPeakTS{t in TECHNOLOGY, r in REGION};
param CapacityFactor{y in YEAR, t in TECHNOLOGY, l in TIMESLICE, r in REGION};
param AvailabilityFactor{y in YEAR, t in TECHNOLOGY, r in REGION};
param OperationalLife{t in TECHNOLOGY, r in REGION};
param ResidualCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
param SalvageFactor{y in YEAR, t in TECHNOLOGY, r in REGION};
param InputActivityRatio{y in YEAR, t in TECHNOLOGY, f in FUEL, m in MODE_OF_OPERATION, r
    in REGION};
param OutputActivityRatio{y in YEAR, t in TECHNOLOGY, f in FUEL, m in MODE_OF_OPERATION,
    r in REGION};
```

Technology Costs

param CapitalCost{y in YEAR, t in TECHNOLOGY, r in REGION};
param VariableCost{y in YEAR, t in TECHNOLOGY, m in MODE_OF_OPERATION, r in REGION};
param FixedCost{y in YEAR, t in TECHNOLOGY, r in REGION};

Capacity Constraints

param TotalAnnualMaxCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMinCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};

Investment Constraints

param TotalAnnualMaxCapacityInvestment{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMinCapacityInvestment{y in YEAR, t in TECHNOLOGY, r in REGION};

Activity Constraints

param TotalTechnologyAnnualActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalTechnologyAnnualActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalTechnologyModelPeriodActivityUpperLimit{t in TECHNOLOGY, r in REGION};
param TotalTechnologyModelPeriodActivityLowerLimit{t in TECHNOLOGY, r in REGION};

Reserve Margin

param ReserveMarginTagTechnology{y in YEAR,t in TECHNOLOGY, r in REGION};
param ReserveMarginTagFuel{y in YEAR,f in FUEL, r in REGION};
param ReserveMargin{y in YEAR, r in REGION};

RE Generation Target

param RETagTechnology{y in YEAR,t in TECHNOLOGY, r in REGION};
param RETagFuel{y in YEAR,f in FUEL, r in REGION};
param REMinProductionTarget{y in YEAR, r in REGION};

Emissions & Penalties

param EmissionActivityRatio{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in MODE_OF_OPERATION, r in REGION};
param EmissionsPenalty{y in YEAR, e in EMISSION, r in REGION};
param AnnualExogenousEmission{y in YEAR, e in EMISSION, r in REGION};
param AnnualEmissionLimit{y in YEAR, e in EMISSION, r in REGION};
param ModelPeriodExogenousEmission{e in EMISSION, r in REGION};
param ModelPeriodEmissionLimit{e in EMISSION, r in REGION};

MODEL VARIABLES

Demand

var RateOfDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var Demand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;

Capacity Variables

```
var NewCapacity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var AccumulatedNewCapacity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var TotalCapacityAnnual{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
```

Activity Variables

```
var RateOfActivity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, m in MODE_OF_OPERATION, r
    in REGION} >= 0;
var RateOfTotalActivity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION} >= 0;
var TotalTechnologyAnnualActivity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var TotalAnnualTechnologyActivityByMode{y in YEAR, t in TECHNOLOGY,m in
    MODE_OF_OPERATION,r in REGION}>=0;
var RateOfProductionByTechnologyByMode{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,m in
    MODE_OF_OPERATION,f in FUEL,r in REGION}>= 0;
var RateOfProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in
    REGION}>= 0;
var ProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in
    REGION}>= 0;
var ProductionByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in REGION}>= 0;
var RateOfProduction{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION} >= 0;
var Production{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION} >= 0;
var RateOfUseByTechnologyByMode{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,m in
    MODE_OF_OPERATION,f in FUEL,r in REGION}>= 0;
var RateOfUseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION} >= 0;
var UseByTechnologyAnnual{y in YEAR, t in TECHNOLOGY,f in FUEL, r in REGION}>= 0;
var RateOfUse{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var UseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in REGION}>= 0;
var Use{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var ProductionAnnual{y in YEAR, f in FUEL, r in REGION}>= 0;
var UseAnnual{y in YEAR, f in FUEL, r in REGION}>= 0;
```

Costing Variables

```
var CapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var SalvageValue{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedSalvageValue{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var OperatingCost{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedOperatingCost{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var AnnualVariableOperatingCost{y in YEAR,t in TECHNOLOGY, r in REGION}>= 0;
var AnnualFixedOperatingCost{y in YEAR,t in TECHNOLOGY, r in REGION}>= 0;
var VariableOperatingCost{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION}>= 0;
var TotalDiscountedCost{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var ModelPeriodCostByRegion {r in REGION} >= 0;
```

Reserve Margin

```
var TotalCapacityInReserveMargin{y in YEAR, r in REGION}>= 0;
var DemandNeedingReserveMargin{y in YEAR,l in TIMESLICE, r in REGION}>= 0;
```

RE Gen Target

```
var TotalGenerationByRETechnologies{y in YEAR, r in REGION};
var TotalREProductionAnnual{y in YEAR, r in REGION};
var RETotalDemandOfTargetFuelAnnual{y in YEAR, r in REGION};
var TotalTechnologyModelPeriodActivity{t in TECHNOLOGY, r in REGION};
```

Emissions

```
var AnnualTechnologyEmissionByMode{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
    MODE_OF_OPERATION, r in REGION}>= 0;
var AnnualTechnologyEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in REGION}>= 0;
var AnnualTechnologyEmissionPenaltyByEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in
    REGION}>= 0;
var AnnualTechnologyEmissionsPenalty{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedTechnologyEmissionsPenalty{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var AnnualEmissions{y in YEAR, e in EMISSION, r in REGION}>= 0;
var EmissionsProduction{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
    MODE_OF_OPERATION, r in REGION};
var ModelPeriodEmissions{e in EMISSION, r in REGION}>= 0;
```

OBJECTIVE FUNCTION

```
minimize cost: sum{y in YEAR, t in TECHNOLOGY, r in REGION} TotalDiscountedCost[y,t,r];
```

CONSTRAINTS#

Demand

```
s.t. EQ_SpecifiedDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    SpecifiedAnnualDemand[y,f,r]*SpecifiedDemandProfile[y,l,f,r]/ YearSplit[y,l]=RateOfDemand[y,l,f,r];
```

Capacity Adequacy A

```
s.t. CAa1_TotalNewCapacity{y in YEAR, t in TECHNOLOGY, r in
    REGION}:AccumulatedNewCapacity[y,t,r] = sum{yy in YEAR: y-yy < OperationalLife[t,r] && y-
    yy>=0} NewCapacity[yy,t,r];
s.t. CAa2_TotalAnnualCapacity{y in YEAR, t in TECHNOLOGY, r in REGION}:
    AccumulatedNewCapacity[y,t,r]+ ResidualCapacity[y,t,r] = TotalCapacityAnnual[y,t,r];
s.t. CAa3_TotalActivityOfEachTechnology{y in YEAR, t in TECHNOLOGY, l in TIMESLICE,r in
    REGION}: sum{m in MODE_OF_OPERATION} RateOfActivity[y,l,t,m,r] =
    RateOfTotalActivity[y,l,t,r];
s.t. CAa4_Constraint_Capacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION:
    TechWithCapacityNeededToMeetPeakTS[t,r]<>0}: RateOfTotalActivity[y,l,t,r] <=
    TotalCapacityAnnual[y,t,r] * CapacityFactor[y,t,l,r]*CapacityToActivityUnit[t,r];
```

Capacity Adequacy B

```
s.t. CAb1_PlannedMaintenance{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{l in TIMESLICE}
    RateOfTotalActivity[y,l,t,r]*YearSplit[y,l] <= sum{l in TIMESLICE}
    (TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*YearSplit[y,l])*
    AvailabilityFactor[y,t,r]*CapacityToActivityUnit[t,r];
```

Energy Balance A

```
s.t. EBa1_RateOfFuelProduction1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION}: RateOfActivity[y,l,t,m,r]*OutputActivityRatio[y,t,f,m,r] =
    RateOfProductionByTechnologyByMode[y,l,t,m,f,r];
s.t. EBa2_RateOfFuelProduction2{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, r in
    REGION}: sum{m in MODE_OF_OPERATION} RateOfProductionByTechnologyByMode[y,l,t,m,f,r]
    = RateOfProductionByTechnology[y,l,t,f,r] ;
s.t. EBa3_RateOfFuelProduction3{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: sum{t in
    TECHNOLOGY} RateOfProductionByTechnology[y,l,t,f,r] = RateOfProduction[y,l,f,r];
s.t. EBa4_RateOfFuelUse1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION}: RateOfActivity[y,l,t,m,r]*InputActivityRatio[y,t,f,m,r] =
    RateOfUseByTechnologyByMode[y,l,t,m,f,r];
s.t. EBa5_RateOfFuelUse2{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, r in REGION}:
    sum{m in MODE_OF_OPERATION} RateOfUseByTechnologyByMode[y,l,t,m,f,r] =
    RateOfUseByTechnology[y,l,t,f,r];
s.t. EBa6_RateOfFuelUse3{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: sum{t in
    TECHNOLOGY} RateOfUseByTechnology[y,l,t,f,r] = RateOfUse[y,l,f,r];
s.t. EBa7_EnergyBalanceEachTS1{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfProduction[y,l,f,r]*YearSplit[y,l] = Production[y,l,f,r];
s.t. EBa8_EnergyBalanceEachTS2{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfUse[y,l,f,r]*YearSplit[y,l] = Use[y,l,f,r];
s.t. EBa9_EnergyBalanceEachTS3{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfDemand[y,l,f,r]*YearSplit[y,l] = Demand[y,l,f,r];
s.t. EBa10_EnergyBalanceEachTS4{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    Production[y,l,f,r] >= Demand[y,l,f,r] + Use[y,l,f,r];
```

Energy Balance B

```
s.t. EBb1_EnergyBalanceEachYear1{y in YEAR, f in FUEL, r in REGION}: sum{l in TIMESLICE}
    Production[y,l,f,r] = ProductionAnnual[y,f,r];
s.t. EBb2_EnergyBalanceEachYear2{y in YEAR, f in FUEL, r in REGION}: sum{l in TIMESLICE}
    Use[y,l,f,r] = UseAnnual[y,f,r];
s.t. EBb3_EnergyBalanceEachYear3{y in YEAR, f in FUEL, r in REGION}: ProductionAnnual[y,f,r] >=
    UseAnnual[y,f,r] + AccumulatedAnnualDemand[y,f,r];
```

Accounting Technology Production/Use#

```
s.t. Acc1_FuelProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION}: RateOfProductionByTechnology[y,l,t,f,r] * YearSplit[y,l] = ProductionByTechnology[y,l,t,f,r];
s.t. Acc2_FuelUseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION}: RateOfUseByTechnology[y,l,t,f,r] * YearSplit[y,l] = UseByTechnology[y,l,t,f,r];
s.t. Acc3_AverageAnnualRateOfActivity{y in YEAR,t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION}: sum{l in TIMESLICE}
    RateOfActivity[y,l,t,m,r]*YearSplit[y,l] = TotalAnnualTechnologyActivityByMode[y,t,m,r];
s.t. Acc4_ModelPeriodCostByRegion{r in REGION}:sum{y in YEAR, t in
    TECHNOLOGY}TotalDiscountedCost[y,t,r]=ModelPeriodCostByRegion[r];
```

Capital Costs

```
s.t. CC1_UndiscountedCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}:
    CapitalCost[y,t,r] * NewCapacity[y,t,r] = CapitalInvestment[y,t,r];
```

```
s.t. CC2_DiscountingCapitalInvestmenta{y in YEAR, t in TECHNOLOGY, r in REGION}:
    CapitalInvestment[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy))) =
    DiscountedCapitalInvestment[y,t,r];

# Salvage Value #

s.t. SV1_SalvageValueAtEndOfPeriod1{y in YEAR, t in TECHNOLOGY, r in REGION: (y +
    OperationalLife[t,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRate[t,r]>0}: SalvageValue[y,t,r] =
    CapitalCost[y,t,r]*NewCapacity[y,t,r]*(1-(((1+DiscountRate[t,r])^(max{yy in YEAR} max(yy) - y+1)-
    1)/((1+DiscountRate[t,r])^OperationalLife[t,r]-1)));
s.t. SV2_SalvageValueAtEndOfPeriod2{y in YEAR, t in TECHNOLOGY, r in REGION: (y +
    OperationalLife[t,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRate[t,r]=0}: SalvageValue[y,t,r] =
    CapitalCost[y,t,r]*NewCapacity[y,t,r]*(1-(max{yy in YEAR} max(yy) - y+1)/OperationalLife[t,r]);
s.t. SV3_SalvageValueAtEndOfPeriod3{y in YEAR, t in TECHNOLOGY, r in REGION: (y +
    OperationalLife[t,r]-1) <= (max{yy in YEAR} max(yy))}: SalvageValue[y,t,r] = 0;
s.t. SV4_SalvageValueDiscountedToStartYear{y in YEAR, t in TECHNOLOGY, r in REGION}:
    DiscountedSalvageValue[y,t,r] = SalvageValue[y,t,r]/((1+DiscountRate[t,r])^(1+max{yy in YEAR}
    max(yy)-min{yy in YEAR} min(yy)));

# Operating Costs #

s.t. OC1_OperatingCostsVariable{y in YEAR,l in TIMESLICE, t in TECHNOLOGY, r in REGION}:
    sum{m in MODE_OF_OPERATION}
    TotalAnnualTechnologyActivityByMode[y,t,m,r]*VariableCost[y,t,m,r] =
    AnnualVariableOperatingCost[y,t,r];
s.t. OC2_OperatingCostsFixedAnnual{y in YEAR,t in TECHNOLOGY, r in REGION}:
    TotalCapacityAnnual[y,t,r]*FixedCost[y,t,r] = AnnualFixedOperatingCost[y,t,r];
s.t. OC3_OperatingCostsTotalAnnual{y in YEAR,t in TECHNOLOGY,r in REGION}:
    AnnualFixedOperatingCost[y,t,r]+AnnualVariableOperatingCost[y,t,r] = OperatingCost[y,t,r];
s.t. OC4_DiscountedOperatingCostsTotalAnnual{y in YEAR, t in TECHNOLOGY, r in REGION}:
    OperatingCost[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy)+0.5)) =
    DiscountedOperatingCost[y,t,r];

# Total Discounted Costs #

s.t. TDC1_TotalDiscountedCostByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}:
    DiscountedOperatingCost[y,t,r]+DiscountedCapitalInvestment[y,t,r]+DiscountedTechnologyEmissionsP
    enalty[y,t,r]-DiscountedSalvageValue[y,t,r] = TotalDiscountedCost[y,t,r];

# Total Capacity Constraints #

s.t. TCC1_TotalAnnualMaxCapacityConstraint{y in YEAR, t in TECHNOLOGY,r in REGION:
    TotalAnnualMaxCapacity[y,t,r]<9999 }: TotalCapacityAnnual[y,t,r] <= TotalAnnualMaxCapacity[y,t,r];
s.t. TCC2_TotalAnnualMinCapacityConstraint{y in YEAR, t in TECHNOLOGY,r in REGION:
    TotalAnnualMinCapacity[y,t,r]>0}: TotalCapacityAnnual[y,t,r] >= TotalAnnualMinCapacity[y,t,r];

# New Capacity Constraints #

s.t. NCC1_TotalAnnualMaxNewCapacityConstraint{y in YEAR, t in TECHNOLOGY, r in REGION:
    TotalAnnualMaxCapacityInvestment[y,t,r]<9999}: NewCapacity[y,t,r] <=
    TotalAnnualMaxCapacityInvestment[y,t,r];
s.t. NCC2_TotalAnnualMinNewCapacityConstraint{y in YEAR, t in TECHNOLOGY, r in REGION:
    TotalAnnualMinCapacityInvestment[y,t,r]>0}: NewCapacity[y,t,r] >=
    TotalAnnualMinCapacityInvestment[y,t,r];
```

```
# Annual Activity Constraints #

s.t. AAC1_TotalAnnualTechnologyActivity{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{l in
    TIMESLICE} RateOfTotalActivity[y,l,t,r]*YearSplit[y,l] = TotalTechnologyAnnualActivity[y,t,r];
s.t. AAC2_TotalAnnualTechnologyActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in
    REGION:TotalTechnologyAnnualActivityUpperLimit[y,t,r]<9999}:
    TotalTechnologyAnnualActivity[y,t,r] <= TotalTechnologyAnnualActivityUpperLimit[y,t,r] ;
s.t. AAC3_TotalAnnualTechnologyActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION:
    TotalTechnologyAnnualActivityLowerLimit[y,t,r]>0}: TotalTechnologyAnnualActivity[y,t,r] >=
    TotalTechnologyAnnualActivityLowerLimit[y,t,r] ;

# Total Activity Constraints #

s.t. TAC1_TotalModelHorizonTechnologyActivity{t in TECHNOLOGY, r in REGION}: sum{y in YEAR}
    TotalTechnologyAnnualActivity[y,t,r] = TotalTechnologyModelPeriodActivity[t,r];
s.t. TAC2_TotalModelHorizonTechnologyActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in
    REGION:TotalTechnologyModelPeriodActivityUpperLimit[t,r]<9999}:
    TotalTechnologyModelPeriodActivity[t,r] <= TotalTechnologyModelPeriodActivityUpperLimit[t,r] ;
s.t. TAC3_TotalModelHorizonTechnologyActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in
    REGION: TotalTechnologyModelPeriodActivityLowerLimit[t,r]>0}:
    TotalTechnologyModelPeriodActivity[t,r] >= TotalTechnologyModelPeriodActivityLowerLimit[t,r] ;

# Reserve Margin Constraint        #

s.t. RM1_ReserveMargin_TechologiesIncluded_In_Activity_Units{y in YEAR, l in TIMESLICE, r in
    REGION}: sum {t in TECHNOLOGY} TotalCapacityAnnual[y,t,r]
    *ReserveMarginTagTechnology[y,t,r] * CapacityToActivityUnit[t,r] = TotalCapacityInReserveMargin[y,r];
s.t. RM2_ReserveMargin_FuelsIncluded{y in YEAR, l in TIMESLICE, r in REGION}: sum {f in FUEL}
    RateOfProduction[y,l,f,r] * ReserveMarginTagFuel[y,f,r] = DemandNeedingReserveMargin[y,l,r];
s.t. RM3_ReserveMargin_Constraint{y in YEAR, l in TIMESLICE, r in REGION}:
    DemandNeedingReserveMargin[y,l,r] * ReserveMargin[y,r]<= TotalCapacityInReserveMargin[y,r];

# RE Production Target #

s.t. RE1_FuelProductionByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in
    REGION}: sum{l in TIMESLICE} ProductionByTechnology[y,l,t,f,r] =
    ProductionByTechnologyAnnual[y,t,f,r];
s.t. RE2_TechIncluded{y in YEAR, r in REGION}: sum{t in TECHNOLOGY, f in FUEL}
    ProductionByTechnologyAnnual[y,t,f,r]*RETagTechnology[y,t,r] = TotalREProductionAnnual[y,r];
s.t. RE3_FuelIncluded{y in YEAR, r in REGION}: sum{l in TIMESLICE, f in FUEL}
    RateOfDemand[y,l,f,r]*YearSplit[y,l]*RETagFuel[y,f,r] = RETotalDemandOfTargetFuelAnnual[y,r];
s.t. RE4_EnergyConstraint{y in YEAR, r in
    REGION}:REMinProductionTarget[y,r]*RETotalDemandOfTargetFuelAnnual[y,r] <=
    TotalREProductionAnnual[y,r];
s.t. RE5_FuelUseByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in REGION}: sum{l
    in TIMESLICE} RateOfUseByTechnology[y,l,t,f,r]*YearSplit[y,l] = UseByTechnologyAnnual[y,t,f,r];

# Emissions Accounting #

s.t. E1_AnnualEmissionProductionByMode{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
    MODE_OF_OPERATION, r in REGION:EmissionActivityRatio[y,t,e,m,r]<>0}:
    EmissionActivityRatio[y,t,e,m,r]*TotalAnnualTechnologyActivityByMode[y,t,m,r]=AnnualTechnologyEm
    issionByMode[y,t,e,m,r];
```

```
s.t. E2_AnnualEmissionProduction{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in REGION}:
    sum{m in MODE_OF_OPERATION} AnnualTechnologyEmissionByMode[y,t,e,m,r] =
    AnnualTechnologyEmission[y,t,e,r];
s.t. E3_EmissionsPenaltyByTechAndEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in
    REGION}: AnnualTechnologyEmission[y,t,e,r]*EmissionsPenalty[y,e,r] =
    AnnualTechnologyEmissionPenaltyByEmission[y,t,e,r];
s.t. E4_EmissionsPenaltyByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{e in
    EMISSION} AnnualTechnologyEmissionPenaltyByEmission[y,t,e,r] =
    AnnualTechnologyEmissionsPenalty[y,t,r];
s.t. E5_DiscountedEmissionsPenaltyByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}:
    AnnualTechnologyEmissionsPenalty[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy)+0.5)) =
    DiscountedTechnologyEmissionsPenalty[y,t,r];
s.t. E6_EmissionsAccounting1{y in YEAR, e in EMISSION, r in REGION}: sum{t in TECHNOLOGY}
    AnnualTechnologyEmission[y,t,e,r] = AnnualEmissions[y,e,r];
s.t. E7_EmissionsAccounting2{e in EMISSION, r in REGION}: sum{y in YEAR} AnnualEmissions[y,e,r] =
    ModelPeriodEmissions[e,r]- ModelPeriodExogenousEmission[e,r];
s.t. E8_AnnualEmissionsLimit{y in YEAR, e in EMISSION, r in REGION}:
    AnnualEmissions[y,e,r]+AnnualExogenousEmission[y,e,r] <= AnnualEmissionLimit[y,e,r];
s.t. E9_ModelPeriodEmissionsLimit{e in EMISSION, r in REGION}: ModelPeriodEmissions[e,r] <=
    ModelPeriodEmissionLimit[e,r] ;
```

```
solve;
end;
```

Annex C.2 Prioritising Demand Types, Demand Shifting and Storage

The code below considers the integration of all code additions at once. To increase readability and for consistency with the main document, the code modifications are arranged by blocks of functionality as opposed to parameters, variables and constraints. When adding these blocks to the code of OSeMOSYS as described under *Annex C.1 Variability in Electricity Generation*, it is recommended to group all parameters and model variables, followed by the objective function and the constraints. Parameters and variables mentioned under both (as indicated by the sub-heading), Prioritising Demand Types and Demand Shifting, only need to be added once.

Annex C.2.1 Prioritising Demand Types

PARAMETERS

Common to both, Prioritising Demand Types and Demand Shifting

```
param SpecifiedDailyFlexibleDemand{y in YEAR, fdt in FLEXIBLEDEMANDTYPE, ls in SEASON, ld in
    DAYTYPE, f in FUEL, r in REGION};
param SpecifiedDailyFlexibleDemandProfile{y in YEAR, fdt in FLEXIBLEDEMANDTYPE, ls in SEASON,
    ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION};
param DiscountRateDemand>=0;
```

Specific to Prioritising Demand Types

```
param MaxShareUnmetDemand{y in YEAR, ftd in FLEXIBLEDEMANDTYPE, f in FUEL, r in
    REGION}>=0;
param PriceOfUnmetDemand{y in YEAR, ftd in FLEXIBLEDEMANDTYPE, f in FUEL, r in
    REGION}>=0;
```

MODEL VARIABLES

Common to both, Prioritising Demand Types and Demand Shifting

```
var RateOfDailyFlexibleDemand{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>= 0;
```

Specific to Prioritising Demand Types

```
var RateOfUnmetDemand{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>=0;
var UnmetDemand{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, l in TIMESLICE, f in FUEL, r in
    REGION}>=0;
var UnmetDemandAnnual{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, f in FUEL, r in REGION}>=0;
var CostOfUnmetDemand{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION}>=0;
var DiscountedCostOfUnmetDemand{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION}>=0;
```

CONSTRAINTS

```
s.t. D3_SpecifiedFlexibleDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    SpecifiedDailyFlexibleDemand[y,fdt,ls,ld,f,r]*SpecifiedDailyFlexibleDemandProfile[y,fdt,ls,ld,lh,f,r] /
    DaySplit[y,lh] = RateOfDailyFlexibleDemand[fdt,y,ls,ld,lh,f,r];
s.t. UD1_UpperLimit{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh
    in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    RateOfUnmetDemand[fdt,y,ls,ld,lh,f,r]<=MaxShareUnmetDemand[y,fdt,f,r]*RateOfDailyFlexibleDeman
    d[fdt,y,ls,ld,lh,f,r];
s.t. UD2_UnmetDemandSeasonal{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, l in TIMESLICE, f in
    FUEL, r in REGION}: sum{ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET}
    (RateOfUnmetDemand[fdt,y,ls,ld,lh,f,r]*Conversionls[ls,l]*Conversionld[ld,l]*Conversionlh[lh,l])*YearSpl
    it[y,l] = UnmetDemand[fdt,y,l,f,r];
s.t. UD3_UnmetDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, f in FUEL, r in REGION}:
    sum{l in TIMESLICE} UnmetDemand[fdt,y,l,f,r] = UnmetDemandAnnual[fdt,y,f,r];
```

s.t. UD4_CostOfUnmetDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION}: sum{f in FUEL} UnmetDemandAnnual[fdt,y,f,r]*PriceOfUnmetDemand[y,fdt,f,r] = CostOfUnmetDemand[fdt,y,r];
s.t. UD5_DiscountedCostOfUnmetDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION}: CostOfUnmetDemand[fdt,y,r]/((1+DiscountRateDemand)^(y-min{yy in YEAR} min(yy)+0.5)) = DiscountedCostOfUnmetDemand[fdt,y,r];

Annex C.2.2 *Demand Shifting*

PARAMETERS

Common to both, Prioritising Demand Types and Demand Shifting

param SpecifiedDailyFlexibleDemand{y in YEAR, fdt in FLEXIBLEDEMANDTYPE, ls in SEASON, ld in DAYTYPE, f in FUEL, r in REGION};
param SpecifiedDailyFlexibleDemandProfile{y in YEAR, fdt in FLEXIBLEDEMANDTYPE, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION};
param DiscountRateDemand>=0;

Specific to Demand Shifting

param MaxShareShiftedDemand{y in YEAR, fdt in FLEXIBLEDEMANDTYPE, f in FUEL, r in REGION};
param MaxDelay{fdt in FLEXIBLEDEMANDTYPE}>=0;
param MaxAdvance{fdt in FLEXIBLEDEMANDTYPE}>=0;
param CostFactorShiftedDemand{fdt in FLEXIBLEDEMANDTYPE};

MODEL VARIABLES

Common to both, Prioritising Demand Types and Demand Shifting

var RateOfDailyFlexibleDemand{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>= 0;

Specific to Demand Shifting

var RateOfNetCharge{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION};
var RateOfNetChargeDelayed{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION};
var RateOfNetChargeAdvanced{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION};
var SumOfDailyNetChargeDelayed{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, f in FUEL, r in REGION}>=0;
var SumOfDailyNetChargeAdvanced{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, f in FUEL, r in REGION}>=0;
var CostOfShiftedDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION};
var DiscountedCostOfShiftedDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION};
var RateOfChargeDelayed{ftd in FLEXIBLEDEMANDTYPE, y in YEAR,ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>=0;

```
var RateOfDischargeDelayed{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>=0;
var RateOfChargeAdvanced{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>=0;
var RateOfDischargeAdvanced{ftd in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}>=0;
```

CONSTRAINTS

```
s.t. D3_SpecifiedFlexibleDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    SpecifiedDailyFlexibleDemand[y,fdt,ls,ld,f,r]*SpecifiedDailyFlexibleDemandProfile[y,fdt,ls,ld,lh,f,r] /
    DaySplit[y,lh] = RateOfDailyFlexibleDemand[fdt,y,ls,ld,lh,f,r];
s.t. DS1_RateOfNetCharge{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    RateOfNetChargeDelayed[fdt,y,ls,ld,lh,f,r]+RateOfNetChargeAdvanced[fdt,y,ls,ld,lh,f,r] =
    RateOfNetCharge[fdt,y,ls,ld,lh,f,r];
s.t. DS2_RateOfNetChargeDelayed{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    RateOfChargeDelayed[fdt,y,ls,ld,lh,f,r]-RateOfDischargeDelayed[fdt,y,ls,ld,lh,f,r] =
    RateOfNetChargeDelayed[fdt,y,ls,ld,lh,f,r];
s.t. DS3_RateOfNetChargeAdvanced{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    RateOfChargeAdvanced[fdt,y,ls,ld,lh,f,r]-RateOfDischargeAdvanced[fdt,y,ls,ld,lh,f,r] =
    RateOfNetChargeAdvanced[fdt,y,ls,ld,lh,f,r];
s.t. DS4_MaxShareConstraint{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}:
    RateOfChargeDelayed[fdt,y,ls,ld,lh,f,r]+RateOfChargeAdvanced[fdt,y,ls,ld,lh,f,r] <=
    MaxShareShiftedDemand[y,fdt,f,r]*RateOfDailyFlexibleDemand[fdt,y,ls,ld,lh,f,r];
s.t. DS5_DelayedLoadsDailyBalance{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, f in FUEL, r in REGION}: sum{lh in DAILYTIMEBRACKET}
    RateOfChargeDelayed[fdt,y,ls,ld,lh,f,r]*DaySplit[y,lh] <= sum{lh in DAILYTIMEBRACKET}
    RateOfDischargeDelayed[fdt,y,ls,ld,lh,f,r]*DaySplit[y,lh];
s.t. DS6_DelayedLoadsStorageLevelGreaterZero{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in
    SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}: sum{lhlh in
    DAILYTIMEBRACKET: lh-lhlh>=0} RateOfChargeDelayed[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh] >=
    sum{lhlh in DAILYTIMEBRACKET: lh-lhlh>=0}
    RateOfDischargeDelayed[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh];
s.t. DS7_DelayUpperLimit{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION: lh<=max{lhlh in
    DAILYTIMEBRACKET} max(lhlh)-MaxDelay[fdt]}: sum{lhlh in DAILYTIMEBRACKET: lhlh<=lh}
    RateOfChargeDelayed[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh] <= sum{lhlh in DAILYTIMEBRACKET:
    lhlh<=lh+MaxDelay[fdt]} RateOfDischargeDelayed[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh];
s.t. DS8_AdvancedLoadsDailyBalance{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, f in FUEL, r in REGION}: sum{lh in DAILYTIMEBRACKET}
    RateOfChargeAdvanced[fdt,y,ls,ld,lh,f,r]*DaySplit[y,lh] <= sum{lh in DAILYTIMEBRACKET}
    RateOfDischargeAdvanced[fdt,y,ls,ld,lh,f,r]*DaySplit[y,lh];
s.t. DS9_AdvancedLoadsStorageLevelBelowMaximum{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in
    SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}: sum{lhlh in
    DAILYTIMEBRACKET: lh-lhlh>=0} RateOfChargeAdvanced[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh] <=
    sum{lhlh in DAILYTIMEBRACKET: lh-lhlh>=0}
    RateOfDischargeAdvanced[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh];
s.t. DS10_AdvanceLowerLimit{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION: lh<=max{lhlh in
    DAILYTIMEBRACKET} max(lhlh)-MaxAdvance[fdt]}: sum{lhlh in DAILYTIMEBRACKET:
```

lhlh<=lh+MaxAdvance[fdt]} RateOfChargeAdvanced[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh] >= sum{lhlh in DAILYTIMEBRACKET: lhlh<=lh} RateOfDischargeAdvanced[fdt,y,ls,ld,lhlh,f,r]*DaySplit[y,lhlh];
s.t. DS11_MinimiseDelay{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, f in FUEL, r in REGION}: sum{lhlh in DAILYTIMEBRACKET} DaySplit[y,lhlh]*365*24*sum{lh in DAILYTIMEBRACKET: lhlh-lh>=0}(RateOfChargeDelayed[fdt,y,ls,ld,lh,f,r]-RateOfDischargeDelayed[fdt,y,ls,ld,lh,f,r])*DaySplit[y,lh]*365*24 = SumOfDailyNetChargeDelayed[fdt,y,ls,ld,f,r];
s.t. DS12_MinimiseAdvance{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, f in FUEL, r in REGION}: sum{lhlh in DAILYTIMEBRACKET} DaySplit[y,lhlh]*365*24*sum{lh in DAILYTIMEBRACKET: lhlh-lh>=0}(RateOfDischargeAdvanced[fdt,y,ls,ld,lh,f,r]-RateOfChargeAdvanced[fdt,y,ls,ld,lh,f,r])*DaySplit[y,lh]*365*24 = SumOfDailyNetChargeAdvanced[fdt,y,ls,ld,f,r];
s.t. DS13_CostOfShiftedDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION}: CostFactorShiftedDemand[fdt] * sum{l in TIMESLICE, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL}((SumOfDailyNetChargeDelayed[fdt,y,ls,ld,f,r]+SumOfDailyNetChargeAdvanced[fdt,y,ls,ld,f,r])*DaysInDayType[y,ls,ld])*YearSplit[y,l]*Conversionls[ls,l]*Conversionld[ld,l]*Conversionlh[lh,l]*52 = CostOfShiftedDemand[fdt,y,r];
s.t. DS14_DiscountedCostOfShiftedDemand{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, r in REGION}: CostOfShiftedDemand[fdt,y,r]/((1+DiscountRateDemand)^(y-min{yy in YEAR} min(yy)+0.5)) = DiscountedCostOfShiftedDemand[fdt,y,r];

Annex C.2.3 Storage

PARAMETERS

param TechnologyToStorage{t in TECHNOLOGY, m in MODE_OF_OPERATION, s in STORAGE, r in REGION};
param TechnologyFromStorage{t in TECHNOLOGY, m in MODE_OF_OPERATION, s in STORAGE, r in REGION};
param StorageLevelStart{s in STORAGE, r in REGION};
param StorageMaxChargeRate{s in STORAGE, r in REGION};
param StorageMaxDischargeRate{s in STORAGE, r in REGION};
param MinStorageCharge{s in STORAGE, y in YEAR, r in REGION};
param OperationalLifeStorage{s in STORAGE, r in REGION};
param CapitalCostStorage{s in STORAGE, y in YEAR, r in REGION};
param DiscountRateStorage{s in STORAGE, r in REGION};
param ResidualStorageCapacity{s in STORAGE, y in YEAR, r in REGION};

MODEL VARIABLES

var RateOfStorageCharge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION};
var RateOfStorageDischarge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION};
var NetChargeWithinYear{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION};
var NetChargeWithinDay{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION};
var StorageLevelYearStart{s in STORAGE, y in YEAR, r in REGION} >=0;
var StorageLevelYearFinish{s in STORAGE, y in YEAR, r in REGION} >=0;

```
var StorageLevelSeasonStart{s in STORAGE, y in YEAR, ls in SEASON, r in REGION} >=0;
var StorageLevelDayTypeStart{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r in
    REGION} >=0;
var StorageLevelDayTypeFinish{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r in
    REGION} >=0;
var StorageLowerLimit{s in STORAGE, y in YEAR, r in REGION}>=0;
var StorageUpperLimit{s in STORAGE, y in YEAR, r in REGION} >=0;
var AccumulatedNewStorageCapacity{s in STORAGE, y in YEAR, r in REGION} >=0;
var NewStorageCapacity{s in STORAGE, y in YEAR, r in REGION} >=0;
var CapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var DiscountedCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var SalvageValueStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var DiscountedSalvageValueStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var TotalDiscountedStorageCost{s in STORAGE, y in YEAR, r in REGION} >=0;
```

CONSTRAINTS

Storage Equations

```
s.t. S1_RateOfStorageCharge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{t in TECHNOLOGY, m in
    MODE_OF_OPERATION, l in TIMESLICE:TechnologyToStorage[t,m,s,r]>0}
    RateOfActivity[y,l,t,m,r] * TechnologyToStorage[t,m,s,r] * Conversionls[ls,l] * Conversionld[ld,l] *
    Conversionlh[lh,l] = RateOfStorageCharge[s,y,ls,ld,lh,r];
s.t. S2_RateOfStorageDischarge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{t in TECHNOLOGY, m in
    MODE_OF_OPERATION, l in TIMESLICE:TechnologyFromStorage[t,m,s,r]>0}
    RateOfActivity[y,l,t,m,r] * TechnologyFromStorage[t,m,s,r] * Conversionls[ls,l] * Conversionld[ld,l] *
    Conversionlh[lh,l] = RateOfStorageDischarge[s,y,ls,ld,lh,r];
s.t. S3_NetChargeWithinYear{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{l in
    TIMESLICE:Conversionls[ls,l]>0&&Conversionld[ld,l]>0&&Conversionlh[lh,l]>0}
    (RateOfStorageCharge[s,y,ls,ld,lh,r] - RateOfStorageDischarge[s,y,ls,ld,lh,r]) * YearSplit[y,l] *
    Conversionls[ls,l] * Conversionld[ld,l] * Conversionlh[lh,l] = NetChargeWithinYear[s,y,ls,ld,lh,r];
s.t. S4_NetChargeWithinDay{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: (RateOfStorageCharge[s,y,ls,ld,lh,r] -
    RateOfStorageDischarge[s,y,ls,ld,lh,r]) * DaySplit[y,lh] = NetChargeWithinDay[s,y,ls,ld,lh,r];
s.t. S5_and_S6_StorageLevelYearStart{s in STORAGE, y in YEAR, r in REGION}:
     if y = min{yy in YEAR} min(yy) then StorageLevelStart[s,r]
    else StorageLevelYearStart[s,y-1,r] + sum{ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y-1,ls,ld,lh,r]
    = StorageLevelYearStart[s,y,r];
s.t. S7_and_S8_StorageLevelYearFinish{s in STORAGE, y in YEAR, r in REGION}:
    if y < max{yy in YEAR} max(yy) then StorageLevelYearStart[s,y+1,r]
    else StorageLevelYearStart[s,y,r] + sum{ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y,ls,ld,lh,r]
    = StorageLevelYearFinish[s,y,r];
s.t. S9_and_S10_StorageLevelSeasonStart{s in STORAGE, y in YEAR, ls in SEASON, r in REGION}:
    if ls = min{lsls in SEASON} min(lsls) then StorageLevelYearStart[s,y,r]
    else StorageLevelSeasonStart[s,y,ls-1,r] + sum{ld in DAYTYPE, lh in DAILYTIMEBRACKET}
    NetChargeWithinYear[s,y,ls-1,ld,lh,r]
    = StorageLevelSeasonStart[s,y,ls,r];
s.t. S11_and_S12_StorageLevelDayTypeStart{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r
    in REGION}:
    if ld = min{ldld in DAYTYPE} min(ldld) then StorageLevelSeasonStart[s,y,ls,r]
```

```
    else StorageLevelDayTypeStart[s,y,ls,ld-1,r] + sum{lh in DAILYTIMEBRACKET}
    NetChargeWithinDay[s,y,ls,ld-1,lh,r] * DaysInDayType[y,ls,ld-1]
    = StorageLevelDayTypeStart[s,y,ls,ld,r];
s.t. S13_and_S14_and_S15_StorageLevelDayTypeFinish{s in STORAGE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, r in REGION}:
    if ls = max{lsls in SEASON} max(lsls) && ld = max{ldld in DAYTYPE} max(ldld) then
    StorageLevelYearFinish[s,y,r]
    else if ld = max{ldld in DAYTYPE} max(ldld) then StorageLevelSeasonStart[s,y,ls+1,r]
    else StorageLevelDayTypeFinish[s,y,ls,ld+1,r] - sum{lh in DAILYTIMEBRACKET}
    NetChargeWithinDay[s,y,ls,ld+1,lh,r] * DaysInDayType[y,ls,ld+1]
    = StorageLevelDayTypeFinish[s,y,ls,ld,r];

                              # Storage Constraints #

s.t. SC1_LowerLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: 0 <= (StorageLevelDayTypeStart[s,y,ls,ld,r]+sum{lhlh in DAILYTIMEBRACKET:lh-
    lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];
s.t. SC1_UpperLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: (StorageLevelDayTypeStart[s,y,ls,ld,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0}
    NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;
s.t. SC2_LowerLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: 0 <= if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeStart[s,y,ls,ld,r]-
    sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld-1,lhlh,r])-
    StorageLowerLimit[s,y,r];
s.t. SC2_UpperLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeStart[s,y,ls,ld,r]-
    sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld-1,lhlh,r])-
    StorageUpperLimit[s,y,r] <= 0;
s.t. SC3_LowerLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}:  0 <= (StorageLevelDayTypeFinish[s,y,ls,ld,r] - sum{lhlh in DAILYTIMEBRACKET:lh-
    lhlh<0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];
s.t. SC3_UpperLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}:  (StorageLevelDayTypeFinish[s,y,ls,ld,r] - sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0}
    NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;
s.t. SC4_LowerLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: 0 <= if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeFinish[s,y,ls,ld-
    1,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-
    StorageLowerLimit[s,y,r];
s.t. SC4_UpperLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeFinish[s,y,ls,ld-
    1,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-
    StorageUpperLimit[s,y,r] <= 0;
s.t. SC5_MaxChargeConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: RateOfStorageCharge[s,y,ls,ld,lh,r] <=
    StorageMaxChargeRate[s,r];
```

```
s.t. SC6_MaxDischargeConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: RateOfStorageDischarge[s,y,ls,ld,lh,r] <=
    StorageMaxDischargeRate[s,r];
```

Storage Investments

```
s.t. SI1_StorageUpperLimit{s in STORAGE, y in YEAR, r in REGION}:
    AccumulatedNewStorageCapacity[s,y,r]+ResidualStorageCapacity[s,y,r] = StorageUpperLimit[s,y,r];
s.t. SI2_StorageLowerLimit{s in STORAGE, y in YEAR, r in REGION}:
    MinStorageCharge[s,y,r]*StorageUpperLimit[s,y,r] = StorageLowerLimit[s,y,r];
s.t. SI3_TotalNewStorage{s in STORAGE, y in YEAR, r in REGION}: sum{yy in YEAR: y-yy <
    OperationalLifeStorage[s,r] && y-yy>=0}
    NewStorageCapacity[s,yy,r]=AccumulatedNewStorageCapacity[s,y,r];
s.t. SI4_UndiscountedCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION}:
    CapitalCostStorage[s,y,r] * NewStorageCapacity[s,y,r] = CapitalInvestmentStorage[s,y,r];
s.t. SI5_DiscountingCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION}:
    CapitalInvestmentStorage[s,y,r]/((1+DiscountRateStorage[s,r])^(y-min{yy in YEAR} min(yy))) =
    DiscountedCapitalInvestmentStorage[s,y,r];
s.t. SI6_SalvageValueStorageAtEndOfPeriod1{s in STORAGE, y in YEAR, r in REGION:
    (y+OperationalLifeStorage[s,r]-1) <= (max{yy in YEAR} max(yy))}: 0 = SalvageValueStorage[s,y,r];
s.t. SI7_SalvageValueStorageAtEndOfPeriod2{s in STORAGE, y in YEAR, r in REGION:
    (y+OperationalLifeStorage[s,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRate[s,r]=0}:
    CapitalInvestmentStorage[s,y,r]*(1-(max{yy in YEAR} max(yy) - y+1)/OperationalLifeStorage[s,r]) =
    SalvageValueStorage[s,y,r];
s.t. SI8_SalvageValueStorageAtEndOfPeriod3{s in STORAGE, y in YEAR, r in REGION:
    (y+OperationalLifeStorage[s,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRateStorage[s,r]>0}:
    CapitalInvestmentStorage[s,y,r]*(1-(((1+DiscountRateStorage[s,r])^(max{yy in YEAR} max(yy) - y+1)-
    1)/((1+DiscountRateStorage[s,r])^OperationalLifeStorage[s,r]-1))) = SalvageValueStorage[s,y,r];
s.t. SI9_SalvageValueStorageDiscountedToStartYear{s in STORAGE, y in YEAR, r in REGION}:
    SalvageValueStorage[s,y,r]/((1+DiscountRateStorage[s,r])^(max{yy in YEAR} max(yy)-min{yy in YEAR}
    min(yy)+1)) = DiscountedSalvageValueStorage[s,y,r];
s.t. SI10_TotalDiscountedCostByStorage{s in STORAGE, y in YEAR, r in REGION}:
    DiscountedCapitalInvestmentStorage[s,y,r]-DiscountedSalvageValueStorage[s,y,r] =
    TotalDiscountedStorageCost[s,y,r];
```

Annex C.2.4 Integration into OSeMOSYS

This section contains required modifications of the core code, as described in *'Part A, Chapter 2.3.6: Bringing It All Together'*:

PARAMETERS

```
param SpecifiedAnnualStandardDemand{y in YEAR, f in FUEL, r in REGION};
param SpecifiedAnnualStandardDemandProfile{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION};
```

VARIABLES

```
var RateOfStandardDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
```

OBJECTIVE FUNCTION

minimize cost: sum{y in YEAR, r in REGION} TotalDiscountedCost[y,r];

CONSTRAINTS

s.t. D1_SpecifiedDemand{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: RateOfStandardDemand[y,l,f,r]+sum{fdt in FLEXIBLEDEMANDTYPE, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET}(RateOfDailyFlexibleDemand[fdt,y,ls,ld,lh,f,r]-RateOfNetCharge[fdt,y,ls,ld,lh,f,r]-RateOfUnmetDemand[fdt,y,ls,ld,lh,f,r])*Conversionls[ls,l]*Conversionld[ld,l]*Conversionlh[lh,l]=RateOfDemand[y,l,f,r];

s.t. D2_SpecifiedStandardDemand{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: SpecifiedAnnualStandardDemand[y,f,r]*SpecifiedAnnualStandardDemandProfile[y,l,f,r] / YearSplit[y,l]=RateOfStandardDemand[y,l,f,r];

s.t. D4_and_D5_UpperLimit{fdt in FLEXIBLEDEMANDTYPE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, f in FUEL, r in REGION}: if MaxShareUnmetDemand[y,fdt,f,r] >= MaxShareShiftedDemand[y,fdt,f,r] then MaxShareUnmetDemand[y,fdt,f,r]*RateOfDailyFlexibleDemand[fdt,y,ls,ld,lh,f,r]-RateOfNetCharge[fdt,y,ls,ld,lh,f,r];

s.t. Acc4_rev_ModelPeriodCostByRegion{r in REGION}:sum{y in YEAR}TotalDiscountedCost[y,r]=ModelPeriodCostByRegion[r];

s.t. TDC1_rev_TotalDiscountedCostByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}: DiscountedOperatingCost[y,t,r]+DiscountedCapitalInvestment[y,t,r]+DiscountedTechnologyEmissionsPenalty[y,t,r]-DiscountedSalvageValue[y,t,r] = TotalDiscountedCostByTechnology[y,t,r];

s.t. TDC2_TotalDiscountedCost{y in YEAR, r in REGION}: sum{t in TECHNOLOGY} TotalDiscountedCostByTechnology[y,t,r]+sum{fdt in FLEXIBLEDEMANDTYPE} DiscountedCostOfUnmetDemand[fdt,y,r]+sum{fdt in FLEXIBLEDEMANDTYPE} DiscountedCostOfShiftedDemand[fdt,y,r]+sum{s in STORAGE} TotalDiscountedStorageCost[s,y,r] = TotalDiscountedCost[y,r];

Annex D OPERATING RESERVE AND CAPACITY CREDIT OF WIND – CODE IMPLEMENTATION

The full model code is given below. First, constraints of the core code of OSeMOSYS are listed. The code enhancements are added afterwards. The code below can effectively be cut and pasted into a GNU MathProg model file and run. The reader is referred to www.osemosys.org for more information and a non-pdf version of the code, as well as sample application files. Note that the '#' symbol precedes a line of code not used in the model and is included for comments.

```
# Model Definition #

# SETS #

set YEAR;
set TECHNOLOGY;
set TIMESLICE;
set FUEL;
set EMISSION;
set MODE_OF_OPERATION;
set REGION;
set SEASON;
set DAYTYPE;
set DAILYTIMEBRACKET;
set FLEXIBLEDEMANDTYPE;
set STORAGE;

# PARAMETERS #

# Global #

param YearSplit{y in YEAR,l in TIMESLICE};
param DiscountRate{t in TECHNOLOGY, r in REGION};
param DaySplit{y in YEAR, lh in DAILYTIMEBRACKET};
param Conversionls{ls in SEASON, l in TIMESLICE};
param Conversionld{ld in DAYTYPE, l in TIMESLICE};
param Conversionlh{lh in DAILYTIMEBRACKET, l in TIMESLICE};
param DaysInDayType{y in YEAR, ls in SEASON, ld in DAYTYPE};
param TradeRoute{y in YEAR, f in FUEL, r in REGION, rr in REGION};

# Demand #

param SpecifiedAnnualDemand{y in YEAR,f in FUEL, r in REGION};
param SpecifiedDemandProfile{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION};
param AccumulatedAnnualDemand{y in YEAR, f in FUEL, r in REGION};
```

Performance

```
param CapacityToActivityUnit{t in TECHNOLOGY, r in REGION};
param TechWithCapacityNeededToMeetPeakTS{t in TECHNOLOGY, r in REGION};
param CapacityFactor{y in YEAR, t in TECHNOLOGY, l in TIMESLICE, r in REGION};
param AvailabilityFactor{y in YEAR, t in TECHNOLOGY, r in REGION};
param OperationalLife{t in TECHNOLOGY, r in REGION};
param ResidualCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
param InputActivityRatio{y in YEAR, t in TECHNOLOGY, f in FUEL, m in MODE_OF_OPERATION, r
    in REGION};
param OutputActivityRatio{y in YEAR, t in TECHNOLOGY, f in FUEL, m in MODE_OF_OPERATION,
    r in REGION};
```

Technology Costs

```
param CapitalCost{y in YEAR, t in TECHNOLOGY, r in REGION};
param VariableCost{y in YEAR, t in TECHNOLOGY, m in MODE_OF_OPERATION, r in REGION};
param FixedCost{y in YEAR, t in TECHNOLOGY, r in REGION};
```

Storage

```
param TechnologyToStorage{t in TECHNOLOGY, m in MODE_OF_OPERATION, s in STORAGE, r in
    REGION};
param TechnologyFromStorage{t in TECHNOLOGY, m in MODE_OF_OPERATION, s in STORAGE, r
    in REGION};
param StorageLevelStart{s in STORAGE, r in REGION};
param StorageMaxChargeRate{s in STORAGE, r in REGION};
param StorageMaxDischargeRate{s in STORAGE, r in REGION};
param MinStorageCharge{s in STORAGE, y in YEAR, r in REGION};
param OperationalLifeStorage{s in STORAGE, r in REGION};
param CapitalCostStorage{s in STORAGE, y in YEAR, r in REGION};
param DiscountRateStorage{s in STORAGE, r in REGION};
param ResidualStorageCapacity{s in STORAGE, y in YEAR, r in REGION};
```

Capacity Constraints

```
param CapacityOfOneTechnologyUnit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMaxCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMinCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
```

Investment Constraints

```
param TotalAnnualMaxCapacityInvestment{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMinCapacityInvestment{y in YEAR, t in TECHNOLOGY, r in REGION};
```

Activity Constraints

```
param TotalTechnologyAnnualActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalTechnologyAnnualActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalTechnologyModelPeriodActivityUpperLimit{t in TECHNOLOGY, r in REGION};
param TotalTechnologyModelPeriodActivityLowerLimit{t in TECHNOLOGY, r in REGION};
```

```
# Reserve Margin #
```

```
param ReserveMarginTagTechnology{y in YEAR,t in TECHNOLOGY, r in REGION};
param ReserveMarginTagFuel{y in YEAR,f in FUEL, r in REGION};
param ReserveMargin{y in YEAR, r in REGION};
```

```
# RE Generation Target #
```

```
param RETagTechnology{y in YEAR,t in TECHNOLOGY, r in REGION};
param RETagFuel{y in YEAR,f in FUEL, r in REGION};
param REMinProductionTarget{y in YEAR, r in REGION};
```

```
# Emissions & Penalties #
```

```
param EmissionActivityRatio{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
    MODE_OF_OPERATION, r in REGION};
param EmissionsPenalty{y in YEAR, e in EMISSION, r in REGION};
param AnnualExogenousEmission{y in YEAR, e in EMISSION, r in REGION};
param AnnualEmissionLimit{y in YEAR, e in EMISSION, r in REGION};
param ModelPeriodExogenousEmission{e in EMISSION, r in REGION};
param ModelPeriodEmissionLimit{e in EMISSION, r in REGION};
```

```
# Wind Capacity Credit #
```

```
param ElectricityForTransmissionTag{f in FUEL, r in REGION};
param WindTechnologyTag{t in TECHNOLOGY, r in REGION};
param PeakElectricityDemandEntered{y in YEAR, r in REGION};
param WindDispersionCoefficient{y in YEAR, r in REGION};
param ReliabilityConventionalPlants{y in YEAR, r in REGION};
param WindCapacityCreditSwitch;
```

```
# Operating Reserve #
```

```
param PrimReserveUpCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param SecReserveUpCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param PrimReserveDownCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param SecReserveDownCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param MinStableOperation{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxPrimReserveUp{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxSecReserveUp{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxPrimReserveDown{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxSecReserveDown{y in YEAR, t in TECHNOLOGY, r in REGION};
param MinSecReserveUpOnline{y in YEAR, r in REGION};
param MinPrimReserveUpOnline{y in YEAR, r in REGION};
param TimeSliceLinkTag{l in TIMESLICE, ll in TIMESLICE, r in REGION};
param MaxOnlineCapReduction{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxGenerationReduction{y in YEAR, t in TECHNOLOGY, r in REGION};
```

```
# MODEL VARIABLES #
```

```
# Demand #
```

```
var RateOfDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var Demand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
```

Storage

```
var RateOfStorageCharge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION};
var RateOfStorageDischarge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION};
var NetChargeWithinYear{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION};
var NetChargeWithinDay{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION};
var StorageLevelYearStart{s in STORAGE, y in YEAR, r in REGION} >=0;
var StorageLevelYearFinish{s in STORAGE, y in YEAR, r in REGION} >=0;
var StorageLevelSeasonStart{s in STORAGE, y in YEAR, ls in SEASON, r in REGION} >=0;
var StorageLevelDayTypeStart{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r in
    REGION} >=0;
var StorageLevelDayTypeFinish{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r in
    REGION} >=0;
var StorageLowerLimit{s in STORAGE, y in YEAR, r in REGION}>=0;
var StorageUpperLimit{s in STORAGE, y in YEAR, r in REGION} >=0;
var AccumulatedNewStorageCapacity{s in STORAGE, y in YEAR, r in REGION} >=0;
var NewStorageCapacity{s in STORAGE, y in YEAR, r in REGION} >=0;
var CapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var DiscountedCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var SalvageValueStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var DiscountedSalvageValueStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var TotalDiscountedStorageCost{s in STORAGE, y in YEAR, r in REGION} >=0;
```

Capacity Variables

```
var NumberOfNewTechnologyUnits{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0,integer;
var NewCapacity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var AccumulatedNewCapacity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var TotalCapacityAnnual{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
```

Activity Variables

```
var RateOfActivity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, m in MODE_OF_OPERATION, r
    in REGION} >= 0;
var RateOfTotalActivity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION} >= 0;
var TotalTechnologyAnnualActivity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var TotalAnnualTechnologyActivityByMode{y in YEAR, t in TECHNOLOGY,m in
    MODE_OF_OPERATION,r in REGION}>=0;
var RateOfProductionByTechnologyByMode{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,m in
    MODE_OF_OPERATION,f in FUEL,r in REGION}>= 0;
var RateOfProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in
    REGION}>= 0;
var ProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in
    REGION}>= 0;
var ProductionByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in REGION}>= 0;
var RateOfProduction{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION} >= 0;
var Production{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION} >= 0;
var RateOfUseByTechnologyByMode{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,m in
    MODE_OF_OPERATION,f in FUEL,r in REGION}>= 0;
```

```
var RateOfUseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION} >= 0;
var UseByTechnologyAnnual{y in YEAR, t in TECHNOLOGY,f in FUEL, r in REGION}>= 0;
var RateOfUse{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var UseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in REGION}>= 0;
var Use{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var Trade{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION, rr in REGION};
var TradeAnnual{y in YEAR, f in FUEL, r in REGION, rr in REGION};
var ProductionAnnual{y in YEAR, f in FUEL, r in REGION}>= 0;
var UseAnnual{y in YEAR, f in FUEL, r in REGION}>= 0;
```

Costing Variables

```
var CapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var SalvageValue{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedSalvageValue{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var OperatingCost{y in YEAR, t in TECHNOLOGY, r in REGION};
var DiscountedOperatingCost{y in YEAR, t in TECHNOLOGY, r in REGION};
var AnnualVariableOperatingCost{y in YEAR,t in TECHNOLOGY, r in REGION};
var AnnualFixedOperatingCost{y in YEAR,t in TECHNOLOGY, r in REGION};
var TotalDiscountedCostByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION};
var TotalDiscountedCost{y in YEAR, r in REGION}>= 0;
var ModelPeriodCostByRegion {r in REGION} >= 0;
```

Reserve Margin

```
var TotalCapacityInReserveMargin{y in YEAR, f in FUEL, r in REGION}>= 0;
var DemandNeedingReserveMargin{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
```

RE Gen Target

```
var TotalREProductionAnnual{y in YEAR, r in REGION};
var RETotalDemandOfTargetFuelAnnual{y in YEAR, r in REGION};
var TotalTechnologyModelPeriodActivity{t in TECHNOLOGY, r in REGION};
```

Emissions

```
var AnnualTechnologyEmissionByMode{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
    MODE_OF_OPERATION, r in REGION}>= 0;
var AnnualTechnologyEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in REGION}>= 0;
var AnnualTechnologyEmissionPenaltyByEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in
    REGION}>= 0;
var AnnualTechnologyEmissionsPenalty{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedTechnologyEmissionsPenalty{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var AnnualEmissions{y in YEAR, e in EMISSION, r in REGION}>= 0;
var ModelPeriodEmissions{e in EMISSION, r in REGION}>= 0;
```

Wind Capacity Credit

```
var PeakElectricityDemandCalculated{y in YEAR, r in REGION} >= 0;
var WindPenetration{y in YEAR, r in REGION} >= 0;
var WindCapacityCreditCalculated{y in YEAR, r in REGION} >= 0;
var Segment1Tag {y in YEAR, r in REGION} binary;
```

```
var Segment2Tag {y in YEAR, r in REGION} binary;
var Segment3Tag {y in YEAR, r in REGION} binary;
var Segment4Tag {y in YEAR, r in REGION} binary;
var Segment5Tag {y in YEAR, r in REGION} binary;
var Segment6Tag {y in YEAR, r in REGION} binary;
var Segment1Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment2Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment3Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment4Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment5Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment6Fraction {y in YEAR, r in REGION} >=0 <=1;
var WindAverageCapacityFactor{y in YEAR, r in REGION} >= 0;
var WindCapacityCreditEntered{y in YEAR, r in REGION};
```

```
# Operating Reserve #
```

```
var PrimReserveDownByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION}
    >= 0;
var SecReserveDownByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION} >=
    0;
var SecReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION} >=0;
var PrimReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION} >=0;
var OnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION};
```

```
# OBJECTIVE FUNCTION #
```

```
minimize cost: sum{y in YEAR, r in REGION} TotalDiscountedCost[y,r];
```

```
# CONSTRAINTS#
```

```
# Demand #
```

```
s.t. EQ_SpecifiedDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    SpecifiedAnnualDemand[y,f,r]*SpecifiedDemandProfile[y,l,f,r] / YearSplit[y,l] = RateOfDemand[y,l,f,r];
```

```
# Capacity Adequacy A #
```

```
s.t. CAa1_TotalNewCapacity{y in YEAR, t in TECHNOLOGY, r in
    REGION}:AccumulatedNewCapacity[y,t,r] = sum{yy in YEAR: y-yy < OperationalLife[t,r] && y-
    yy>=0} if CapacityOfOneTechnologyUnit[y,t,r]=0 then NewCapacity[yy,t,r] else
    CapacityOfOneTechnologyUnit[yy,t,r]*NumberOfNewTechnologyUnits[yy,t,r];
s.t. CAa2_TotalAnnualCapacity{y in YEAR, t in TECHNOLOGY, r in REGION}:
    AccumulatedNewCapacity[y,t,r]+ ResidualCapacity[y,t,r] = TotalCapacityAnnual[y,t,r];
s.t. CAa3_TotalActivityOfEachTechnology{y in YEAR, t in TECHNOLOGY, l in TIMESLICE,r in
    REGION}: sum{m in MODE_OF_OPERATION} RateOfActivity[y,l,t,m,r] =
    RateOfTotalActivity[y,l,t,r];
s.t. CAa4_Constraint_Capacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION:
    TechWithCapacityNeededToMeetPeakTS[t,r]<>0}: RateOfTotalActivity[y,l,t,r] <=
    TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*CapacityToActivityUnit[t,r];
```

```
# Capacity Adequacy B #
```

```
s.t. CAb1_PlannedMaintenance{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{l in TIMESLICE}
    RateOfTotalActivity[y,l,t,r]*YearSplit[y,l] <= sum{l in TIMESLICE}
```

```
(TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*YearSplit[y,l])*
    AvailabilityFactor[y,t,r]*CapacityToActivityUnit[t,r];
```

Energy Balance A

```
s.t. EBa1_RateOfFuelProduction1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION: OutputActivityRatio[y,t,f,m,r] <>0}:
    RateOfActivity[y,l,t,m,r]*OutputActivityRatio[y,t,f,m,r] =
    RateOfProductionByTechnologyByMode[y,l,t,m,f,r];
s.t. EBa2_RateOfFuelProduction2{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, r in
    REGION}: sum{m in MODE_OF_OPERATION: OutputActivityRatio[y,t,f,m,r] <>0}
    RateOfProductionByTechnologyByMode[y,l,t,m,f,r] = RateOfProductionByTechnology[y,l,t,f,r] ;
s.t. EBa3_RateOfFuelProduction3{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: sum{t in
    TECHNOLOGY} RateOfProductionByTechnology[y,l,t,f,r] = RateOfProduction[y,l,f,r];
s.t. EBa4_RateOfFuelUse1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION:InputActivityRatio[y,t,f,m,r]<>0}:
    RateOfActivity[y,l,t,m,r]*InputActivityRatio[y,t,f,m,r] = RateOfUseByTechnologyByMode[y,l,t,m,f,r];
s.t. EBa5_RateOfFuelUse2{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, r in REGION}:
    sum{m in MODE_OF_OPERATION:InputActivityRatio[y,t,f,m,r]<>0}
    RateOfUseByTechnologyByMode[y,l,t,m,f,r] = RateOfUseByTechnology[y,l,t,f,r];
s.t. EBa6_RateOfFuelUse3{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: sum{t in
    TECHNOLOGY} RateOfUseByTechnology[y,l,t,f,r] = RateOfUse[y,l,f,r];
s.t. EBa7_EnergyBalanceEachTS1{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfProduction[y,l,f,r]*YearSplit[y,l] = Production[y,l,f,r];
s.t. EBa8_EnergyBalanceEachTS2{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfUse[y,l,f,r]*YearSplit[y,l] = Use[y,l,f,r];
s.t. EBa9_EnergyBalanceEachTS3{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfDemand[y,l,f,r]*YearSplit[y,l] = Demand[y,l,f,r];
s.t. EBa10_EnergyBalanceEachTS4{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION, rr in
    REGION}: Trade[y,l,f,r,rr] = -Trade[y,l,f,rr,r];
s.t. EBa11_EnergyBalanceEachTS5{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
    Production[y,l,f,r] >= Demand[y,l,f,r] + Use[y,l,f,r] + sum{rr in REGION}
    Trade[y,l,f,r,rr]*TradeRoute[y,f,r,rr];
```

Energy Balance B

```
s.t. EBb1_EnergyBalanceEachYear1{y in YEAR, f in FUEL, r in REGION}: sum{l in TIMESLICE}
    Production[y,l,f,r] = ProductionAnnual[y,f,r];
s.t. EBb2_EnergyBalanceEachYear2{y in YEAR, f in FUEL, r in REGION}: sum{l in TIMESLICE}
    Use[y,l,f,r] = UseAnnual[y,f,r];
s.t. EBb3_EnergyBalanceEachYear3{y in YEAR, f in FUEL, r in REGION, rr in REGION}: sum{l in
    TIMESLICE} Trade[y,l,f,r,rr] = TradeAnnual[y,f,r,rr];
s.t. EBb4_EnergyBalanceEachYear4{y in YEAR, f in FUEL, r in REGION}: ProductionAnnual[y,f,r] >=
    UseAnnual[y,f,r] + sum{rr in REGION} TradeAnnual[y,f,r,rr]*TradeRoute[y,f,r,rr] +
    AccumulatedAnnualDemand[y,f,r];
```

Accounting Technology Production/Use

```
s.t. Acc1_FuelProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION}: RateOfProductionByTechnology[y,l,t,f,r] * YearSplit[y,l] = ProductionByTechnology[y,l,t,f,r];
s.t. Acc2_FuelUseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION}: RateOfUseByTechnology[y,l,t,f,r] * YearSplit[y,l] = UseByTechnology[y,l,t,f,r];
```

```
s.t. Acc3_AverageAnnualRateOfActivity{y in YEAR,t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION}: sum{l in TIMESLICE}
    RateOfActivity[y,l,t,m,r]*YearSplit[y,l] = TotalAnnualTechnologyActivityByMode[y,t,m,r];
s.t. Acc4_ModelPeriodCostByRegion{r in REGION}:sum{y in YEAR}TotalDiscountedCost[y,r] =
    ModelPeriodCostByRegion[r];
```

Storage Equations

```
s.t. S1_RateOfStorageCharge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{t in TECHNOLOGY, m in
    MODE_OF_OPERATION, l in TIMESLICE:TechnologyToStorage[t,m,s,r]>0}
    RateOfActivity[y,l,t,m,r] * TechnologyToStorage[t,m,s,r] * Conversionls[ls,l] * Conversionld[ld,l] *
    Conversionlh[lh,l] = RateOfStorageCharge[s,y,ls,ld,lh,r];
s.t. S2_RateOfStorageDischarge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{t in TECHNOLOGY, m in
    MODE_OF_OPERATION, l in TIMESLICE:TechnologyFromStorage[t,m,s,r]>0}
    RateOfActivity[y,l,t,m,r] * TechnologyFromStorage[t,m,s,r] * Conversionls[ls,l] * Conversionld[ld,l] *
    Conversionlh[lh,l] = RateOfStorageDischarge[s,y,ls,ld,lh,r];
s.t. S3_NetChargeWithinYear{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{l in
    TIMESLICE:Conversionls[ls,l]>0&&Conversionld[ld,l]>0&&Conversionlh[lh,l]>0}
    (RateOfStorageCharge[s,y,ls,ld,lh,r] - RateOfStorageDischarge[s,y,ls,ld,lh,r]) * YearSplit[y,l] *
    Conversionls[ls,l] * Conversionld[ld,l] * Conversionlh[lh,l] = NetChargeWithinYear[s,y,ls,ld,lh,r];
s.t. S4_NetChargeWithinDay{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: (RateOfStorageCharge[s,y,ls,ld,lh,r] -
    RateOfStorageDischarge[s,y,ls,ld,lh,r]) * DaySplit[y,lh] = NetChargeWithinDay[s,y,ls,ld,lh,r];
s.t. S5_and_S6_StorageLevelYearStart{s in STORAGE, y in YEAR, r in REGION}:
     if y = min{yy in YEAR} min(yy) then StorageLevelStart[s,r]
    else StorageLevelYearStart[s,y-1,r] + sum{ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y-1,ls,ld,lh,r]
    = StorageLevelYearStart[s,y,r];
s.t. S7_and_S8_StorageLevelYearFinish{s in STORAGE, y in YEAR, r in REGION}:
    if y < max{yy in YEAR} max(yy) then StorageLevelYearStart[s,y+1,r]
    else StorageLevelYearStart[s,y,r] + sum{ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y,ls,ld,lh,r]
    = StorageLevelYearFinish[s,y,r];
s.t. S9_and_S10_StorageLevelSeasonStart{s in STORAGE, y in YEAR, ls in SEASON, r in REGION}:
    if ls = min{lsls in SEASON} min(lsls) then StorageLevelYearStart[s,y,r]
    else StorageLevelSeasonStart[s,y,ls-1,r] + sum{ld in DAYTYPE, lh in DAILYTIMEBRACKET}
    NetChargeWithinYear[s,y,ls-1,ld,lh,r]
    = StorageLevelSeasonStart[s,y,ls,r];
s.t. S11_and_S12_StorageLevelDayTypeStart{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r
    in REGION}:
    if ld = min{ldld in DAYTYPE} min(ldld) then StorageLevelSeasonStart[s,y,ls,r]
    else StorageLevelDayTypeStart[s,y,ls,ld-1,r] + sum{lh in DAILYTIMEBRACKET}
    NetChargeWithinDay[s,y,ls,ld-1,lh,r] * DaysInDayType[y,ls,ld-1]
    = StorageLevelDayTypeStart[s,y,ls,ld,r];
s.t. S13_and_S14_and_S15_StorageLevelDayTypeFinish{s in STORAGE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, r in REGION}:
    if ls = max{lsls in SEASON} max(lsls) && ld = max{ldld in DAYTYPE} max(ldld) then
    StorageLevelYearFinish[s,y,r]
    else if ld = max{ldld in DAYTYPE} max(ldld) then StorageLevelSeasonStart[s,y,ls+1,r]
    else StorageLevelDayTypeFinish[s,y,ls,ld+1,r] - sum{lh in DAILYTIMEBRACKET}
    NetChargeWithinDay[s,y,ls,ld+1,lh,r] * DaysInDayType[y,ls,ld+1]
    = StorageLevelDayTypeFinish[s,y,ls,ld,r];
```

```
# Storage Constraints #

s.t. SC1_LowerLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: 0 <= (StorageLevelDayTypeStart[s,y,ls,ld,r]+sum{lhlh in DAILYTIMEBRACKET:lh-
    lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];
s.t. SC1_UpperLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: (StorageLevelDayTypeStart[s,y,ls,ld,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0}
    NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;
s.t. SC2_LowerLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: 0 <= if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeStart[s,y,ls,ld,r]-
    sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld-1,lhlh,r])-
    StorageLowerLimit[s,y,r];
s.t. SC2_UpperLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInFirstWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeStart[s,y,ls,ld,r]-
    sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld-1,lhlh,r])-
    StorageUpperLimit[s,y,r] <= 0;
s.t. SC3_LowerLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}:  0 <= (StorageLevelDayTypeFinish[s,y,ls,ld,r] - sum{lhlh in DAILYTIMEBRACKET:lh-
    lhlh<0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];
s.t. SC3_UpperLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}:  (StorageLevelDayTypeFinish[s,y,ls,ld,r] - sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0}
    NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;
s.t. SC4_LowerLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: 0 <= if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeFinish[s,y,ls,ld-
    1,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-
    StorageLowerLimit[s,y,r];
s.t. SC4_UpperLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInLastWeek Constraint{s in
    STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in
    REGION}: if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeFinish[s,y,ls,ld-
    1,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-
    StorageUpperLimit[s,y,r] <= 0;
s.t. SC5_MaxChargeConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: RateOfStorageCharge[s,y,ls,ld,lh,r] <=
    StorageMaxChargeRate[s,r];
s.t. SC6_MaxDischargeConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: RateOfStorageDischarge[s,y,ls,ld,lh,r] <=
    StorageMaxDischargeRate[s,r];
```

```
# Storage Investments #

s.t. SI1_StorageUpperLimit{s in STORAGE, y in YEAR, r in REGION}:
    AccumulatedNewStorageCapacity[s,y,r]+ResidualStorageCapacity[s,y,r] = StorageUpperLimit[s,y,r];
s.t. SI2_StorageLowerLimit{s in STORAGE, y in YEAR, r in REGION}:
    MinStorageCharge[s,y,r]*StorageUpperLimit[s,y,r] = StorageLowerLimit[s,y,r];
s.t. SI3_TotalNewStorage{s in STORAGE, y in YEAR, r in REGION}: sum{yy in YEAR: y-yy <
    OperationalLifeStorage[s,r] && y-yy>=0}
    NewStorageCapacity[s,yy,r]=AccumulatedNewStorageCapacity[s,y,r];
```

```
s.t. SI4_UndiscountedCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION}:
    CapitalCostStorage[s,y,r] * NewStorageCapacity[s,y,r] = CapitalInvestmentStorage[s,y,r];
s.t. SI5_DiscountingCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION}:
    CapitalInvestmentStorage[s,y,r]/((1+DiscountRateStorage[s,r])^(y-min{yy in YEAR} min(yy))) =
    DiscountedCapitalInvestmentStorage[s,y,r];
s.t. SI6_SalvageValueStorageAtEndOfPeriod1{s in STORAGE, y in YEAR, r in REGION:
    (y+OperationalLifeStorage[s,r]-1) <= (max{yy in YEAR} max(yy))}: 0 = SalvageValueStorage[s,y,r];
s.t. SI7_SalvageValueStorageAtEndOfPeriod2{s in STORAGE, y in YEAR, r in REGION:
    (y+OperationalLifeStorage[s,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRate[s,r]=0}:
    CapitalInvestmentStorage[s,y,r]*(1-(max{yy in YEAR} max(yy) - y+1)/OperationalLifeStorage[s,r]) =
    SalvageValueStorage[s,y,r];
s.t. SI8_SalvageValueStorageAtEndOfPeriod3{s in STORAGE, y in YEAR, r in REGION:
    (y+OperationalLifeStorage[s,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRateStorage[s,r]>0}:
    CapitalInvestmentStorage[s,y,r]*(1-(((1+DiscountRateStorage[s,r])^(max{yy in YEAR} max(yy) - y+1)-
    1)/((1+DiscountRateStorage[s,r])^OperationalLifeStorage[s,r]-1))) = SalvageValueStorage[s,y,r];
s.t. SI9_SalvageValueStorageDiscountedToStartYear{s in STORAGE, y in YEAR, r in REGION}:
    SalvageValueStorage[s,y,r]/((1+DiscountRateStorage[s,r])^(max{yy in YEAR} max(yy)-min{yy in YEAR}
    min(yy)+1)) = DiscountedSalvageValueStorage[s,y,r];
s.t. SI10_TotalDiscountedCostByStorage{s in STORAGE, y in YEAR, r in REGION}:
    DiscountedCapitalInvestmentStorage[s,y,r]-DiscountedSalvageValueStorage[s,y,r] =
    TotalDiscountedStorageCost[s,y,r];
```

Capital Costs

```
s.t. CC1_UndiscountedCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}:
    CapitalCost[y,t,r] * NewCapacity[y,t,r] = CapitalInvestment[y,t,r];
s.t. CC2_DiscountingCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}:
    CapitalInvestment[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy))) =
    DiscountedCapitalInvestment[y,t,r];
```

Salvage Value

```
s.t. SV2rev_SalvageValueAtEndOfPeriod2{y in YEAR, t in TECHNOLOGY, r in REGION: (y +
    OperationalLife[t,r]-1) > (max{yy in YEAR} max(yy))}: SalvageValue[y,t,r] =
    CapitalCost[y,t,r]*NewCapacity[y,t,r]*(1-(max{yy in YEAR} max(yy) - y+1)/OperationalLife[t,r]);
s.t. SV3_SalvageValueAtEndOfPeriod3{y in YEAR, t in TECHNOLOGY, r in REGION: (y +
    OperationalLife[t,r]-1) <= (max{yy in YEAR} max(yy))}: SalvageValue[y,t,r] = 0;
s.t. SV4_SalvageValueDiscountedToStartYear{y in YEAR, t in TECHNOLOGY, r in REGION}:
    DiscountedSalvageValue[y,t,r] = SalvageValue[y,t,r]/((1+DiscountRate[t,r])^(1+max{yy in YEAR}
    max(yy)-min{yy in YEAR} min(yy)));
```

Operating Costs

```
s.t. OC1_OperatingCostsVariable{y in YEAR,l in TIMESLICE, t in TECHNOLOGY, r in REGION}:
    sum{m in MODE_OF_OPERATION}
    TotalAnnualTechnologyActivityByMode[y,t,m,r]*VariableCost[y,t,m,r] =
    AnnualVariableOperatingCost[y,t,r];
s.t. OC2_OperatingCostsFixedAnnual{y in YEAR,t in TECHNOLOGY, r in REGION}:
    TotalCapacityAnnual[y,t,r]*FixedCost[y,t,r] = AnnualFixedOperatingCost[y,t,r];
s.t. OC3_OperatingCostsTotalAnnual{y in YEAR,t in TECHNOLOGY,r in REGION}:
    AnnualFixedOperatingCost[y,t,r]+AnnualVariableOperatingCost[y,t,r] = OperatingCost[y,t,r];
s.t. OC4_DiscountedOperatingCostsTotalAnnual{y in YEAR, t in TECHNOLOGY, r in REGION}:
    OperatingCost[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy)+0.5)) =
    DiscountedOperatingCost[y,t,r];
```

```
# Total Discounted Costs #

s.t. TDC1_TotalDiscountedCostByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}:
    DiscountedOperatingCost[y,t,r]+DiscountedCapitalInvestment[y,t,r]+DiscountedTechnologyEmissionsP
    enalty[y,t,r]-DiscountedSalvageValue[y,t,r]+sum{l in TIMESLICE}
    (SecReserveDownByTechnology[y,l,t,r]+PrimReserveDownByTechnology[y,l,t,r])*(-0.00001) =
    TotalDiscountedCostByTechnology[y,t,r];
s.t. TDC2_TotalDiscountedCost{y in YEAR, r in REGION}: sum{t in TECHNOLOGY}
    TotalDiscountedCostByTechnology[y,t,r]+sum{s in STORAGE} TotalDiscountedStorageCost[s,y,r] =
    TotalDiscountedCost[y,r];
```

```
# Total Capacity Constraints #

s.t. TCC1_TotalAnnualMaxCapacityConstraint{y in YEAR, t in TECHNOLOGY,r in REGION}:
    TotalCapacityAnnual[y,t,r] <= TotalAnnualMaxCapacity[y,t,r];
s.t. TCC2_TotalAnnualMinCapacityConstraint{y in YEAR, t in TECHNOLOGY,r in REGION:
    TotalAnnualMinCapacity[y,t,r]>0}: TotalCapacityAnnual[y,t,r] >= TotalAnnualMinCapacity[y,t,r];
```

```
# New Capacity Constraints #

s.t. NCC1_TotalAnnualMaxNewCapacityConstraint{y in YEAR, t in TECHNOLOGY, r in REGION}:
    NewCapacity[y,t,r] <= TotalAnnualMaxCapacityInvestment[y,t,r];
s.t. NCC2_TotalAnnualMinNewCapacityConstraint{y in YEAR, t in TECHNOLOGY, r in REGION:
    TotalAnnualMinCapacityInvestment[y,t,r]>0}: NewCapacity[y,t,r] >=
    TotalAnnualMinCapacityInvestment[y,t,r];
```

```
# Annual Activity Constraints #

s.t. AAC1_TotalAnnualTechnologyActivity{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{l in
    TIMESLICE} RateOfTotalActivity[y,l,t,r]*YearSplit[y,l] = TotalTechnologyAnnualActivity[y,t,r];
s.t. AAC2_TotalAnnualTechnologyActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in REGION}:
    TotalTechnologyAnnualActivity[y,t,r] <= TotalTechnologyAnnualActivityUpperLimit[y,t,r] ;
s.t. AAC3_TotalAnnualTechnologyActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION:
    TotalTechnologyAnnualActivityLowerLimit[y,t,r]>0}: TotalTechnologyAnnualActivity[y,t,r] >=
    TotalTechnologyAnnualActivityLowerLimit[y,t,r] ;
```

```
# Total Activity Constraints #

s.t. TAC1_TotalModelHorizonTechnologyActivity{t in TECHNOLOGY, r in REGION}: sum{y in YEAR}
    TotalTechnologyAnnualActivity[y,t,r] = TotalTechnologyModelPeriodActivity[t,r];
s.t. TAC2_TotalModelHorizonTechnologyActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in
    REGION}: TotalTechnologyModelPeriodActivity[t,r] <=
    TotalTechnologyModelPeriodActivityUpperLimit[t,r] ;
s.t. TAC3_TotalModelHorizenTechnologyActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in
    REGION: TotalTechnologyModelPeriodActivityLowerLimit[t,r]>0}:
    TotalTechnologyModelPeriodActivity[t,r] >= TotalTechnologyModelPeriodActivityLowerLimit[t,r] ;
```

```
# Reserve Margin Constraint #

s.t. RM1_ReserveMargin_TechologiesIncluded_In_Activity_Units{y in YEAR, f in FUEL, r in REGION}:
    sum {t in TECHNOLOGY, m in MODE_OF_OPERATION: OutputActivityRatio[y,t,f,m,r] <>0}
    TotalCapacityAnnual[y,t,r]*ReserveMarginTagTechnology[y,t,r]*CapacityToActivityUnit[t,r] =
    TotalCapacityInReserveMargin[y,f,r];
```

```
s.t. RM2_ReserveMargin_FuelsIncluded{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}:
    RateOfProduction[y,l,f,r]*ReserveMarginTagFuel[y,f,r] = DemandNeedingReserveMargin[y,l,f,r];
s.t. RM3_ReserveMargin_Constraint{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}:
    DemandNeedingReserveMargin[y,l,f,r]*ReserveMargin[y,r] <= TotalCapacityInReserveMargin[y,f,r];

# RE Production Target #

s.t. RE1_FuelProductionByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in
    REGION}: sum{l in TIMESLICE} ProductionByTechnology[y,l,t,f,r] =
    ProductionByTechnologyAnnual[y,t,f,r];
s.t. RE2_TechIncluded{y in YEAR, r in REGION}: sum{t in TECHNOLOGY, f in FUEL}
    ProductionByTechnologyAnnual[y,t,f,r]*RETagTechnology[y,t,r] = TotalREProductionAnnual[y,r];
s.t. RE3_FuelIncluded{y in YEAR, r in REGION}: sum{l in TIMESLICE, f in FUEL}
    RateOfDemand[y,l,f,r]*YearSplit[y,l]*RETagFuel[y,f,r] = RETotalDemandOfTargetFuelAnnual[y,r];
s.t. RE4_EnergyConstraint{y in YEAR, r in
    REGION}:REMinProductionTarget[y,r]*RETotalDemandOfTargetFuelAnnual[y,r] <=
    TotalREProductionAnnual[y,r];
s.t. RE5_FuelUseByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in REGION}: sum{l
    in TIMESLICE} RateOfUseByTechnology[y,l,t,f,r]*YearSplit[y,l] = UseByTechnologyAnnual[y,t,f,r];

# Emissions Accounting #

s.t. E1_AnnualEmissionProductionByMode{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
    MODE_OF_OPERATION, r in REGION:EmissionActivityRatio[y,t,e,m,r]<>0}:
    EmissionActivityRatio[y,t,e,m,r]*TotalAnnualTechnologyActivityByMode[y,t,m,r]=AnnualTechnologyEm
    issionByMode[y,t,e,m,r];
s.t. E2_AnnualEmissionProduction{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in REGION}:
    sum{m in MODE_OF_OPERATION} AnnualTechnologyEmissionByMode[y,t,e,m,r] =
    AnnualTechnologyEmission[y,t,e,r];
s.t. E3_EmissionsPenaltyByTechAndEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in
    REGION}: AnnualTechnologyEmission[y,t,e,r]*EmissionsPenalty[y,e,r] =
    AnnualTechnologyEmissionPenaltyByEmission[y,t,e,r];
s.t. E4_EmissionsPenaltyByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{e in
    EMISSION} AnnualTechnologyEmissionPenaltyByEmission[y,t,e,r] =
    AnnualTechnologyEmissionsPenalty[y,t,r];
s.t. E5_DiscountedEmissionsPenaltyByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}:
    AnnualTechnologyEmissionsPenalty[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy)+0.5)) =
    DiscountedTechnologyEmissionsPenalty[y,t,r];
s.t. E6_EmissionsAccounting1{y in YEAR, e in EMISSION, r in REGION}: sum{t in TECHNOLOGY}
    AnnualTechnologyEmission[y,t,e,r] = AnnualEmissions[y,e,r];
s.t. E7_EmissionsAccounting2{e in EMISSION, r in REGION}: sum{y in YEAR} AnnualEmissions[y,e,r] =
    ModelPeriodEmissions[e,r] - ModelPeriodExogenousEmission[e,r];
s.t. E8_AnnualEmissionsLimit{y in YEAR, e in EMISSION, r in REGION}:
    AnnualEmissions[y,e,r]+AnnualExogenousEmission[y,e,r] <= AnnualEmissionLimit[y,e,r];
s.t. E9_ModelPeriodEmissionsLimit{e in EMISSION, r in REGION}: ModelPeriodEmissions[e,r] <=
    ModelPeriodEmissionLimit[e,r] ;

# Wind Capacity Credit #

s.t. WCC1_PeakDemand{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION:
    SpecifiedDemandProfile[y,l,f,r] / YearSplit[y,l] >= max{ll in TIMESLICE}
    max(SpecifiedDemandProfile[y,ll,f,r] / YearSplit[y,ll]) && ElectricityForTransmissionTag[f,r]=1 &&
    WindTechnologyTag[t,r]=1}: (RateOfDemand[y,l,f,r] + RateOfUse[y,l,f,r])/CapacityToActivityUnit[t,r] =
    PeakElectricityDemandCalculated[y,r];
```

```
s.t. WCC2_WindPenetration{y in YEAR, t in TECHNOLOGY, r in REGION: WindTechnologyTag[t,r]=1}:
    TotalCapacityAnnual[y,t,r]/PeakElectricityDemandEntered[y,r] = WindPenetration[y,r];
s.t. WCC3_WindAverageCapacityFactor{y in YEAR, t in TECHNOLOGY, r in REGION:
    WindTechnologyTag[t,r]=1}: sum{l in TIMESLICE} CapacityFactor[y,t,l,r]*YearSplit[y,l] =
    WindAverageCapacityFactor[y,r];
s.t. WCC4_WindCapacityCreditEntered{y in YEAR,t in TECHNOLOGY, r in REGION:
    WindTechnologyTag[t,r]=1}: ReserveMarginTagTechnology[y,t,r] = WindCapacityCreditEntered[y,r];
s.t. WCC5_SegmentSelection{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment1Tag[y,r] +
    Segment2Tag[y,r] + Segment3Tag[y,r] + Segment4Tag[y,r] + Segment5Tag[y,r] + Segment6Tag[y,r] = 1;
s.t. WCC6a_SegmentFraction1{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
    Segment1Fraction[y,r] <= Segment1Tag[y,r];
s.t. WCC6b_SegmentFraction2{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
    Segment2Fraction[y,r] <= Segment2Tag[y,r];
s.t. WCC6c_SegmentFraction3{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
    Segment3Fraction[y,r] <= Segment3Tag[y,r];
s.t. WCC6d_SegmentFraction4{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
    Segment4Fraction[y,r] <= Segment4Tag[y,r];
s.t. WCC6e_SegmentFraction5{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
    Segment5Fraction[y,r] <= Segment5Tag[y,r];
s.t. WCC6f_SegmentFraction6{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
    Segment6Fraction[y,r] <= Segment6Tag[y,r];
s.t. WCC7_WindPenetrationSegment{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
(Segment1Fraction[y,r]*1 + Segment2Tag[y,r]*1 + Segment2Fraction[y,r]*4 + Segment3Tag[y,r]*5 +
    Segment3Fraction[y,r]*5 + Segment4Tag[y,r]*10 + Segment4Fraction[y,r]*10 + Segment5Tag[y,r]*20 +
    Segment5Fraction[y,r]*15 + Segment6Tag[y,r]*35 + Segment6Fraction[y,r]*965)/100 =
    WindPenetration[y,r];
s.t. WCC8_WindCapacityCredit{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: 1/100*(
    (Segment1Tag[y,r] + Segment2Tag[y,r])*32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in
    TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/
    ReliabilityConventionalPlants[y,r]*(1+3.26*WindDispersionCoefficient[y,r]) + Segment2Fraction[y,r]*
    (32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY:
    WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]*
    (3.26*WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(5-1))-1))) +
    Segment3Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in
    TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/
    ReliabilityConventionalPlants[y,r]* (1+3.26*WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+
    WindDispersionCoefficient[y,r])*(5-1)))) + Segment3Fraction[y,r] *(32.8/(0.306 +
    WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY:
    WindTechnologyTag[t,r]> 0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/
    ReliabilityConventionalPlants[y,r]*(3.26* WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+
    WindDispersionCoefficient[y,r])*(10-1))-exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(5-1))))) +
    Segment4Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in
    TECHNOLOGY: WindTechnologyTag[t,r]> 0}
    CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]* (1+3.26*
    WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(10-1)))) +
    Segment4Fraction[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in
    TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/
    ReliabilityConventionalPlants[y,r]*(3.26*WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+
    WindDispersionCoefficient[y,r])*(20-1))-exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(10-1)))))
    + Segment5Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in
    TECHNOLOGY: WindTechnologyTag[t,r]>0}
    CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]*(1+3.26*
    WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(20-1)))) +
    Segment5Fraction[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in
    TECHNOLOGY: WindTechnologyTag[t,r]> 0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/
```

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    ReliabilityConventionalPlants[y,r]*(3.26* WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+
    WindDispersionCoefficient[y,r])*(35-1))-exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(20-1)))))
    + Segment6Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in
    TECHNOLOGY: WindTechnologyTag[t,r]> 0}
    CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]* (1+3.26*
    WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(35-1)))) =
    WindCapacityCreditCalculated[y,r];

                         # Meeting Operating Reserve Demands #
________________________________________________________________________________

s.t. R1_PrimDemandUp{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION: f = "PrimReserveUp"}:
    sum{t in TECHNOLOGY} RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >=
    PrimReserveUpCapacityDemand[y,l,r];
s.t. R2_SecDemandUp{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION: f = "SecReserveUp"}:
    sum{t in TECHNOLOGY} RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >=
    SecReserveUpCapacityDemand[y,l,r];
s.t. R3_PrimDemandDown{y in YEAR, l in TIMESLICE, r in REGION}: {t in TECHNOLOGY}
    PrimReserveDownByTechnology[y,l,t,r]/CapacityToActivityUnit[t,r] >=
    PrimReserveDownCapacityDemand[y,l,r];
s.t. R4_SecDemandDown{y in YEAR, l in TIMESLICE, r in REGION}: {t in TECHNOLOGY}
    SecReserveDownByTechnology[y,l,t,r]/CapacityToActivityUnit[t,r] >=
    SecReserveDownCapacityDemand[y,l,r];

                         # Considering Ramping Characteristics #
________________________________________________________________________________

s.t. R5_MaxOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
    REGION}:OnlineCapacity[y,l,t,r] <= TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r];
s.t. R6_MaxPrimCapacityDown{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION}:
    PrimReserveDownByTechnology[y,l,t,r] <=
    OnlineCapacity[y,l,t,r]*MaxPrimReserveDown[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R7_MaxSecCapacityDown{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION}:
    SecReserveDownByTechnology[y,l,t,r] <=
    OnlineCapacity[y,l,t,r]*MaxSecReserveDown[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R8_MaxPrimCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION:
    f = "PrimReserveUp" && MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
    MinStableOperation[y,t,r]}:RateOfProductionByTechnology[y,l,t,f,r] <=
    TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*MaxPrimReserveUp[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R9_MaxSecCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: f
    = "SecReserveUp" && MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r]}: RateOfProductionByTechnology[y,l,t,f,r] <=
    TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*MaxSecReserveUp[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R10_MinElecGeneration1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: ElectricityForTransmissionTag[f,r]=1 && MaxSecReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r] &&
    (MaxPrimReserveDown[y,t,r]>0 || MaxPrimReserveUp[y,t,r]>0 || MaxSecReserveDown[y,t,r]>0 ||
    MaxSecReserveUp[y,t,r]>0)}: PrimReserveDownByTechnology[y,l,t,r] +
    SecReserveDownByTechnology[y,l,t,r] <= RateOfProductionByTechnology[y,l,t,f,r];
s.t. R11_MinOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION:
    ElectricityForTransmissionTag[f,r]=1 && MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r]}:
    RateOfProductionByTechnology[y,l,t,f,r] <= OnlineCapacity[y,l,t,r]*CapacityToActivityUnit[t,r];
```

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s.t. R12_MinElecGeneration2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: ElectricityForTransmissionTag[f,r]=1 && MaxSecReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r]}:
    OnlineCapacity[y,l,t,r]*MinStableOperation[y,t,r]*CapacityToActivityUnit[t,r] <=
    RateOfProductionByTechnology[y,l,t,f,r];
s.t. R13_MaxPrimCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: f = "PrimReserveUp" && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r])}: RateOfProductionByTechnology[y,l,t,f,r] <=
    OnlineCapacity[y,l,t,r]*MaxPrimReserveUp[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R14_MaxSecCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION:
    f = "SecReserveUp" && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) && (MaxSecReserveDown[y,t,r] <
    MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] <
    MinStableOperation[y,t,r])}:RateOfProductionByTechnology[y,l,t,f,r] <=
    OnlineCapacity[y,l,t,r]*MaxSecReserveUp[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R15_MinElecGeneration{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION:
    ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) && (MaxSecReserveDown[y,t,r] <
    MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] < MinStableOperation[y,t,r]) &&
    (MaxPrimReserveDown[y,t,r]>0 || MaxPrimReserveUp[y,t,r]>0 || MaxSecReserveDown[y,t,r]>0 ||
    MaxSecReserveUp[y,t,r]>0)}:
    OnlineCapacity[y,l,t,r]*MinStableOperation[y,t,r]*CapacityToActivityUnit[t,r] +
    PrimReserveDownByTechnology[y,l,t,r] + SecReserveDownByTechnology[y,l,t,r] <=
    RateOfProductionByTechnology[y,l,t,f,r];
s.t. R16_MinOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, ff in FUEL, fff
    in FUEL, r in REGION: ff = "PrimReserveUp" && fff = "SecReserveUp" &&
    ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) && (MaxSecReserveDown[y,t,r] <
    MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] < MinStableOperation[y,t,r])}:
    RateOfProductionByTechnology[y,l,t,f,r] + RateOfProductionByTechnology[y,l,t,ff,r] +
    RateOfProductionByTechnology[y,l,t,fff,r] <= OnlineCapacity[y,l,t,r]*CapacityToActivityUnit[t,r];
s.t. R17_MinOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, ff in FUEL, r
    in REGION: ff = "PrimReserveUp" && ElectricityForTransmissionTag[f,r]=1 &&
    (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] <
    MinStableOperation[y,t,r]) && MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r] && (MaxPrimReserveDown[y,t,r]>0 ||
    MaxSecReserveDown[y,t,r]>0 || MaxPrimReserveUp[y,t,r]>0 || MaxSecReserveUp[y,t,r]>0)}:
    RateOfProductionByTechnology[y,l,t,f,r] + RateOfProductionByTechnology[y,l,t,ff,r] <=
    OnlineCapacity[y,l,t,r]*CapacityToActivityUnit[t,r];
s.t. R18_MinElecGeneration{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION:
    ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) && MaxSecReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxPrimReserveDown[y,t,r] > 0}:PrimReserveDownByTechnology[y,l,t,r]*(MinStableOperation[y,t,r] +
    MaxPrimReserveDown[y,t,r])/MaxPrimReserveDown[y,t,r] + SecReserveDownByTechnology[y,l,t,r] <=
    RateOfProductionByTechnology[y,l,t,f,r];

                    # Minimum online upward reserve calculations #

s.t. R19_MinPrimReserveUpOnline{y in YEAR, l in TIMESLICE, r in REGION}:
    PrimReserveUpCapacityDemand[y,l,r]*MinPrimReserveUpOnline[y,r] <= sum{t in TECHNOLOGY}
    PrimReserveUpOnline[y,l,t,r];
s.t. R20_MinSecReserveUpOnline{y in YEAR, l in TIMESLICE, r in REGION}:
    SecReserveUpCapacityDemand[y,l,r]*MinSecReserveUpOnline[y,r] <= sum{t in TECHNOLOGY}
    SecReserveUpOnline[y,l,t,r];
```

```
s.t. R21_MaxPrimReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: f = "PrimReserveUp" && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r])}:
    RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] = PrimReserveUpOnline[y,l,t,r];
s.t. R22_MaxSecReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: f = "SecReserveUp" && (MaxSecReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
    MaxSecReserveUp[y,t,r] < MinStableOperation[y,t,r])}:
    RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] = SecReserveUpOnline[y,l,t,r];
s.t. R23_MaxPrimReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: f = "PrimReserveUp" && (MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r])}:
    RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >= PrimReserveUpOnline[y,l,t,r];
s.t. R24_MaxSecReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: f = "SecReserveUp" && (MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
    MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r])}:
    RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >= SecReserveUpOnline[y,l,t,r];
s.t. R25_MaxReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] ||
    MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
    MinStableOperation[y,t,r])}: OnlineCapacity[y,l,t,r] -
    RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >= PrimReserveUpOnline[y,l,t,r] +
    SecReserveUpOnline[y,l,t,r];
s.t. R26_MaxPrimReserveUpOnline2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION:
    MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >=
    MinStableOperation[y,t,r]}: OnlineCapacity[y,l,t,r]*MaxPrimReserveUp[y,t,r] >=
    PrimReserveUpOnline[y,l,t,r];
s.t. R27_MaxSecReserveUpOnline2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION:
    MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
    MinStableOperation[y,t,r]}: OnlineCapacity[y,l,t,r]*MaxSecReserveUp[y,t,r] >=
    SecReserveUpOnline[y,l,t,r];

                    # Maximum changes in online capacity and generation #
-----------------------------------------------------------------------------

s.t. R28_MaxCycling{y in YEAR, l in TIMESLICE, ll in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: ElectricityForTransmissionTag[f,r]=1 && TimeSliceLinkTag[l,ll,r]<>0}:
    OnlineCapacity[y,ll,t,r]*(1-MaxOnlineCapReduction[y,t,r])*TimeSliceLinkTag[l,ll,r] <=
    OnlineCapacity[y,l,t,r];
s.t. R29_MaxGenerationChange{y in YEAR, l in TIMESLICE, ll in TIMESLICE, t in TECHNOLOGY, f in
    FUEL, r in REGION: ElectricityForTransmissionTag[f,r]=1 && TimeSliceLinkTag[l,ll,r]<>0}:
    (RateOfProductionByTechnology[y,ll,t,f,r] -
    OnlineCapacity[y,ll,t,r]*MaxGenerationReduction[y,t,r]*CapacityToActivityUnit[t,r])*TimeSliceLinkTag[l,l
    l,r] <= RateOfProductionByTechnology[y,l,t,f,r];

-----------------------------------------------------------------------------

solve
end;

-----------------------------------------------------------------------------
```

Annex E DETAILED TEST CASE ASSUMPTIONS

This annex presents more detail regarding the assumptions applied for the illustrative case study assessed in Section 4 of Part B of this thesis. They are in addition to the information provided in Section 4.1.

Demand was assumed to be price-inelastic and increase from 78.2 to 126.0 GW during the peak-periods from 2010 until 2040. Four seasons were modelled with one representative day each, split up in an equally long day- and night-time (Table 16). The underlying annual growth rate of the demand was set to 1.6%. This equals the average growth rate of European OECD countries over the period 1990 – 2020 [368].

Table 16
Demand in each time slice [GW]

	Winter Day	Winter Night	Spring Day	Spring Night	Summer Day	Summer Night	Autumn Day	Autumn Night
2010	78.2	56.8	66.1	44.1	73.5	47.8	71.4	48.4
2040	126.0	91.4	106.5	70.9	118.4	77.0	114.9	77.9

Primary reserve was assumed to be available within seconds and secondary reserve within 15 minutes. As suggested in Section 2.2.1 of Part B of this thesis, a half an hour time horizon was chosen to estimate primary reserve requirements and a four hour time horizon for secondary reserve. Reserve requirements were considered based on some of the metrics provided in that section. The standard deviation of the demand forecast error was assumed to be 1% over the half an hour and +-2% over the four hour time horizon. The standard deviation of the wind forecast error was assumed to be +-1.4% and +-6% over the same time horizons. The total reserve requirements were calculated for each time slice as three times the sum of the root-mean-square of these standard deviations, plus the outage of the single largest plant for upward reserve requirements. The largest plant was assumed to have a capacity of 1.6 GW[182].

---

182 The Capacity Outage Probability Table (COPT) macro developed by Lang [453] was used to estimate the likeliness of an outage to occur which is greater than this largest plant. For this purpose, the plant type and size mix was aligned to the German power system [454]. The outage probability was calculated based on unavailability data from VGB PowerTech and Eurelectric [365]. Their forced outage definition includes outages which are shiftable up to 12

This results in maximum primary upward reserve requirements of 4.0 GW in 2010 and 6.5 GW in 2040. The downward reserve demand increase from 2.4 GW – 4.9 GW over the same time horizon. For secondary reserve, the peak requirements increase from 7.0 GW – 17.1 GW for upward reserve and 5.4 GW – 15.5 GW for downward reserve. These significant increases are due to the gain in wind power generation throughout the modelling period. One third of all upward reserve was required to be provided by online plants[183].

Table 17
Generation Input Data

	Units	Technology						
		Nuclear	Coal	Wind	CCGT-fl	CCGT-pl	OCGT-fl	OCGT-pl
Capital Cost	Million USD/GW	4100	2130	2350	1070	1070	740	740
Variable Cost	USD/MWh	24.0	6.0	21.9	4.5	4.5	7.7	7.7
Fuel Costs	USD/GJ	incl. in var. costs	3.60	0.00	9.76	9.76	9.76	9.76
Availability (Max. Capacity Factor)	-	0.85	0.85	0.26	0.85	0.85	0.85	0.85
Expected Life Time	Years	60	40	25	30	30	30	30
Efficiency	%	33	41	100	57	54	43	41
Initial Capacities	GW	45	35	15	0	0	0	0
Retirement of Initial Capacities After Every 5 Years	%	10	15	20	-	-	-	-
Minimum Stable Operation	% of Capacity	50.0	45.0	0.0	42.0	42.0	55.0	55.0
Max. Prim. Upward Reserve	% of Capacity	2.0	6.4	0.0	7.0	7.0	10.0	10.0
Max. Prim. Downward Reserve	% of Capacity	2.0	6.4	5.0	7.0	7.0	10.0	10.0
Max. Sec. Upward Reserve	% of Capacity	10.0	30.8	0.0	0.0	37.5	0.0	100.0
Max. Sec. Downward Reserve	% of Capacity	10.0	30.8	100.0	0.0	37.5	0.0	100.0

Table 17 provides an overview of the modelled technologies and their characteristics, which are largely based on the performance of existing plants. For simplicity, assumptions about future performance improvements were avoided. All capacity factors, expected life times, efficiencies and cost data, apart from reserve costs, were taken from average country data provided by the IEA et al. [306]. A very small negative cost was assigned to the provision of reserve.

hours. In line with a study by dena [455], this data was adjusted to account for the shorter reserve timeframes and divided by the 'Mean Time To Repair' to derive the probability of an outage in a specific plant [375,456]. Based on the COPT calculations, the resulting likeliness of an outage greater than 1.6 GW was found to be 2.0% within the four hour timeframe and 0.03% within the half an hour timeframe.

183 If reserve requirements were normally distributed and reserve demand was entered as three times the standard deviation, this would ensure that 68% of all upward reserve requirements are provided by online plants.

This ensures that the model calculates the available reserve, which might be higher than the required reserve.

Minimum stable operation levels and reserve contributions by nuclear power plants were aligned with NEA data [370]. For wind, this data was drawn from publications by Tsili and Papathanassiou, De Vos et al. and Vestas [371–373]. Other minimum stable operations levels were derived from work by Carraretto and Deane et al. [49,374]. Other contributions to reserve were taken from data provided by Meibom et al. [375]. These values were increased for the primary reserve provision by combined cycle gas turbines, assuming half of them would be able to operate in frequency response mode with ramping characteristics as outlined by Balling, and Pickard and Meinecke [376,377]. Where not explicitly available in the mentioned literature, data for the maximum secondary reserve contribution was derived by multiplying the ramping rates over the secondary reserve timeframe of 15 minutes.

The applied transmission and distribution losses of 6.1% equal those of the OECD Europe region [369]. The wind dispersion coefficient of 0.56 was aligned with the value mentioned for Denmark (refer to Section 2.1.2 of Part B). In this illustrative application, the availability of wind power in each time slice was set equal to the yearly capacity factor. Variations of wind power within each time slice were considered implicitly within the calculation of the reserve requirements. A detailed modelling of minimum and maximum generation from wind power based on probabilistic assessments was however outside the scope of this application. IPCC Tier 1 default emission factors were assigned to coal and natural gas. They were derived from the technology and environmental database within LEAP[184]. The overall reserve margin of the power system was set to 20% and a discount rate of 5% was applied to all expenditures.

The sinking fund depreciation used in the core code of OSeMOSYS was replaced by a straight-line depreciation. This was done by commenting out the salvage value and storage investment equations (SV1 & SI8). In (SV2 & SI7) the condition was removed that the discount rate has to equal zero for these equations to apply [39,101]. Unlike the straight-line depreciation, the sinking fund depreciation is lowest in the first years of an investment [457]. Therefore, technologies with larger investment costs might become profitable in later years,

[184] As mentioned, LEAP uses OSeMOSYS optimisation features for the calculation of power plant capacity expansions. It does so by writing an input data file for OSeMOSYS, running OSeMOSYS and then importing the results back into LEAP. This input data file was used for the first model case presented in Section 4.2.1 of Part B of this thesis.

given their higher salvage value at the end of the modelling period. The straight-line depreciation was applied to avoid this influence of the salvage value.

Annex F THE IRISH PUMPED STORAGE HYDROPOWER PLANT – CODE IMPLEMENTATION

The code implementation for the Irish pumped storage hydropower plant is given below. The code below can effectively be cut and pasted into the GNU MathProg model file provided in Annex D. The storage parameters, variables and constraints provided below need to be added to the model file, whereas modified constraints replace there precursors. The reader is referred to www.osemosys.org for more information. Note that the '#' symbol precedes a line of code not used in the model and is included for comments.

```
# STORAGE PARAMETERS #

param StorageTag{t in TECHNOLOGY, f in FUEL, r in REGION};
param StorageEfficiency{t in TECHNOLOGY, r in REGION};
param StorageLimit{t in TECHNOLOGY, r in REGION};
param TimeslicesInSeason{ls in SEASON, l in TIMESLICE, r in REGION};
param DaysWithinSeason{ls in SEASON, r in REGION};

# STORAGE VARIABLES#

var StorageCharging{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in REGION} >=0;

# STORAGE CONSTRAINTS#

s.t. DS1_StorageCharging{y in YEAR, ls in SEASON, t in TECHNOLOGY, f in FUEL, r in REGION}:
    sum{l in TIMESLICE}
    ProductionByTechnology[y,l,t,f,r]*TimeslicesInSeason[ls,l,r]/StorageEfficiency[t,r]* StorageTag[t,f,r] =
    sum{l in TIMESLICE} StorageCharging[y,l,t,f,r]*TimeslicesInSeason[ls,l,r];
s.t. DS2_MaxChargingPerDay{y in YEAR, ls in SEASON, t in TECHNOLOGY, f in FUEL, r in REGION:
    StorageTag[t,f,r]=1}: (sum{l in TIMESLICE}
    ProductionByTechnology[y,l,t,f,r]*TimeslicesInSeason[ls,l,r]) <=
    StorageLimit[t,r]*DaysWithinSeason[ls,r];

# MODIFIED CONSTRAINTS#

s.t. EBa4rev_RateOfFuelUse1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION:InputActivityRatio[y,t,f,m,r]<>0 || StorageTag[t,f,r]<>0}:
    RateOfActivity[y,l,t,m,r]*InputActivityRatio[y,t,f,m,r] + StorageCharging[y,l,t,f,r]/YearSplit[y,l] =
    RateOfUseByTechnologyByMode[y,l,t,m,f,r];
s.t. CAa4rev_Constraint_Capacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION:
    TechWithCapacityNeededToMeetPeakTS[t,r]<>0}: RateOfTotalActivity[y,l,t,r] + sum{f in FUEL}
    StorageCharging[y,l,t,f,r]/YearSplit[y,l] <=
    TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*CapacityToActivityUnit[t,r];
s.t. EBa1reva_RateOfFuelProduction1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
    MODE_OF_OPERATION, r in REGION: OutputActivityRatio[y,t,f,m,r] <>0 && not(sum{ff in
    FUEL} StorageTag[t,ff,r] = 1 && f = "PrimReserveUp")}:
```

```
RateOfActivity[y,l,t,m,r]*OutputActivityRatio[y,t,f,m,r] =
    RateOfProductionByTechnologyByMode[y,l,t,m,f,r];
s.t. EBa1revb_RateOfFuelProduction1b{y in YEAR, l in TIMESLICE, f in FUEL, ff in FUEL, t in
    TECHNOLOGY, m in MODE_OF_OPERATION, r in REGION: StorageTag[t,f,r] = 1 && ff =
    "PrimReserveUp"}: RateOfActivity[y,l,t,m,r]*OutputActivityRatio[y,t,ff,m,r] +
    StorageCharging[y,l,t,f,r]/YearSplit[y,l] = RateOfProductionByTechnologyByMode[y,l,t,m,ff,r];
s.t. R25rev_MaxReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
    REGION: ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] >=
    MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] ||
    MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
    MinStableOperation[y,t,r])}:
    OnlineCapacity[y,l,t,r] - RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] +
    StorageCharging[y,l,t,f,r]/YearSplit[y,l]/CapacityToActivityUnit[t,r] >= PrimReserveUpOnline[y,l,t,r] +
    SecReserveUpOnline[y,l,t,r];
s.t. R26rev_MaxPrimReserveUpOnline2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION:
    MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >=
    MinStableOperation[y,t,r]}:
    OnlineCapacity[y,l,t,r]*MaxPrimReserveUp[y,t,r] + sum{f in FUEL}
    StorageCharging[y,l,t,f,r]/YearSplit[y,l]/ CapacityToActivityUnit[t,r] >= PrimReserveUpOnline[y,l,t,r];
```

Annex G POWER PLANT DATA FOR CLEWS STUDY ON MAURITIUS

Power Plants	Efficiency	Maximum availability	Capacity credit	Capital cost	Fixed O&M cost	Variable O&M cost	Fuel cost	Life time	Feedstock Fuel
	%	%	%	Mio. USD/MW	1000 USD/MW	USD/MWh	USD/GJ	Years	-
Beau Champ	24	70.3	70.3	2.3	0	7.6	0	30	Coal, Bagasse
Belle Vue	24	65.9	65.9	2.3	48	5.4	1.2	30	Coal, Bagasse
Cascade Ceclie	100	13.2	4.5	4.3	0	5.8	0	30	Hydro
Champagne	100	11.4	90	2.4	0	2.1	10.9	30	Hydro
CTDS	25	91.6	91.6	2.1	48	6.5	2.3	30	Coal
CTSav	24	85	85	2.3	48	5.4	1.2	30	Coal, Bagasse
F.U.E.L.	24	73.3	73.3	2.3	48	5.2	1	30	Coal, Bagasse
Ferney	100	24.6	90	2.4	0	2.1	10.9	30	Hydro
Fort George	44.2	85	95	0.8	35	2.1	10.9	30	Oil
Fort Victoria	42	58	95	0.8	35	2.1	10.9	30	Oil
La Chaumiere	100	85	85	25.5	0	49.4	0	30	Waste
La Ferme	100	12.7	4.4	4.3	0	5.8	0	30	Hydro
La Nicoliere Feeder canal	100	60	60	4.3	0	3.5	0	30	Hydro
Le Val	100	12	4.1	4.3	0	5.8	0	30	Hydro
Magenta	100	20.4	7.1	4.3	0	5.8	0	30	Hydro
Mare Chicose Landfill Gas	100	76	76	2.9	0	33	0.4	30	Biogas
Medine	23	25.5	0	2.3	0	14.3	0	30	Bagasse
Mon Desert Alma	23	36.5	0	2.3	0	8	0	30	Bagasse
Mon Loisir	23	53.5	0	2.3	0	4.9	0	30	Bagasse
Mon Tresor Milling	23	41.3	0	2.3	0	6.4	0	30	Bagasse
New Geothermal	100	86	86	3.4	0	18.2	0	30	Heat
New PV	100	20	0	6	0	33.3	0	30	Solar
Nicolay	26	85	95	0.8	35	2.1	10.9	30	Kerosene
Pointe aux Caves	25	85	85	2.1	48	6.5	2.3	30	Coal
Reduit	100	25	8.6	4.3	0	5.8	0	30	Hydro
Riche En Eau	23	27.1	0	2.3	0	12.2	0	30	Bagasse
Savannah	23	40.1	0	2.3	0	7.3	0	30	Bagasse
St. Louis	39.2	85	95	0.8	35	2.1	10.9	30	Oil
Tamarind Falls	100	26	9	4.3	0	5.8	0	30	Hydro
Thermal not exported to CEB	24	85	85	2.3	48	3.5	0	30	Coal, Bagasse
Union St. Aubin	23	57.3	0	2.3	0	5.1	0	30	Bagasse

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