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Understanding the Impact of Large-Scale Power Grid Architectures on Performance

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UNDERSTANDING THE IMPACT OF LARGE-SCALE POWER GRID ARCHITECTURES ON PERFORMANCE

by

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ABSTRACT

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Grid balancing is a critical system requirement for the power grid in matching the supply to the demand. This balancing has historically been achieved by conventional power generators. However, the increasing level of renewable penetration has brought more variability and uncertainty to the grid (Ela, Diakov et al. 2013, Bessa, Moreira et al. 2014), which has considerable impacts and implications on power system reliability and efficiency, as well as costs. Energy planners have the task of designing infrastructure power systems to provide electricity to the population, wherever and whenever needed. Deciding of the right grid architecture is no easy task, considering consumers' economic, environmental, and security priorities, while making efficient use of existing resources.

In this research, as one contribution, we explore associations between grid architectures and their performance, that is, their ability to meet consumers' concerns. To do this, we first conduct a correlation analysis study. We propose a generative method that captures path dependency by iteratively creating grids, structurally different. The method would generate alternative grid architectures by subjecting an initial grid to a heuristic choice method for decision making over a fixed time horizon. Second, we also conduct a comparative study to evaluate differences in grid performances. We consider two balancing area operation types, presenting different structures and coordination mechanisms. Both studies are performed with the use of a grid simulation model, *Spark!* The aim of this model is to offer a meso-scale solution

that enables the study of very large power systems over long-time horizons, with a sufficient level of fidelity to perform day-to-day grid activities and support architectural questions about the grids of the future. More importantly, the model reconciles long-term planning with short-term grid operations, enabling long-term projections validation via grid operations and response on a daily basis. This is our second contribution.

This dissertation is dedicated to my late father, mother and son.

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CHAPTER 1

INTRODUCTION

A power system is an interconnected network of components for the supply, delivery and consumption of electricity (Adegbululgbe, Fenhann et al. 2007). According to Kaplan (2009), it consists of generation stations, which produce electrical power; transmission lines, which transport electricity from distant sources to demand centers; and distribution system, which provides power to users. Such a system ought to be (1) reliable - power should be delivered whenever, wherever and in whatever quantity needed, (2) economically competitive - power should be generated and delivered in the least expensive manner, and (3) environmentally responsible - power should be generated with the least emission possible (DOE 2015).

Ensuring these three features requires planning. Energy planning consists in developing not only medium to long-range policies to help guide the future of the global energy system (Ngui, Wasike et al. 2011), but also short-term activities helping to perform day-to-day activities (electricity trading, plants dispatch, etc.). In other words, it is the study of the energy system, aiming to provide decision makers with relevant information and assist them in making informed decisions to cover demands, now and in the future. The type of energy we are specifically focusing on is electricity, or power. In this work, those two words are used interchangeably. The most common approach in the power sector to perform planning is to develop an IRP (Integrated Resource Planning). It is a decision making process whose purpose is to suggest ways to meet future power demand by identifying the need for generating capacity and determining the best mix of energy resources (TVA 2015). This practice emerged after the 1970s energy crisis, which brought a period of relatively stable energy prices and stable supply-demand relation to an end.

Prior to this crisis, electricity planning was considerably less complex, given fairly predictable rises in electricity demand with a shift to predominantly larger generating plants (Kagiannas, Didis et al. 2003). Following the crisis, there was an urgent need to diversify energy resources, which led to a more elaborate and integrated planning process, taking into account the demand for electricity, flexibility to market changes, energy provision reliability, environmental impact reduction and risk management of strategies considered (TVA 2015).

Recurrent energy planning issues cited in the literature are (1) the growth in demand for energy, (2) the challenge of energy supply and (3) the concern about energy security and environmental constraints, particularly the challenge of climate change (Safi, Muller et al. 2012). Decision-makers in the power system infrastructure domain have to deal with physical and financial constraints; capacity limitations as well as uncertainties, including unexpected disruptions; changes in demand for electricity; maintenance and investment decisions; and other challenges (Van Dam 2009). These problems are not new, but are still hard to solve, comprehend, and predict given the complexity of the power infrastructure systems. This complexity arises from the diversity of supply and technology options available, the temporal and/or spatial evolutions of technical parameters over medium- to long-term time horizons (Li, Huang et al. 2011, Koltsaklis, Dagoumas et al. 2014). To compound to the complexity even more, the global consensus on climate change is now well established, and the public opinion is becoming increasingly sensitive to sustainability, prompting governments to enforce tighter regulations on greenhouse gases and other pollutant emissions (Pollitt and Sioshansi 2008). As societies pursue the options of diversification of energy sources, generation and distribution infrastructure, the balance between energy, economics, and the environment is needed for sustainable development to take place.

Recent and anticipated trends indicate that renewable resources, particularly wind and solar energy, will be of a consistently growing contribution to global power systems, up to decades (Mai, Drury et al. 2013). It is evident now that formerly marginal renewable technologies like wind and solar are becoming mature and cost effective enough to justify grid scale investments (Khare, Nema et al. 2013). According to Beiter and Tian (2016), renewable sources accounted for more than 24% (5,830 TWh) of all electricity generation worldwide in 2015. In the US, for example, it has been recognized that renewable resource potential exceeds by far any projection of demands in electricity (Hand, Baldwin et al. 2012, Lopez, Roberts et al. 2012). However, unlike conventional fuel-based generation technologies where fuels, (e.g. gas, coal or oil) can be transported (via pipe or trucks) to convenient locations for burning, or stored, renewable energy sources are location and time bound. This poses physical concerns. Typically, power plants are fairly close to populated areas, making the resultant electricity easy to distribute (Mai, Mulcahy et al. 2014). Renewables do not enjoy such privilege. A wind farm can only be installed in a windy area, or a solar plant, in a sunny area, and electricity generated is transported via transmission lines. In addition, the intermittent nature of renewables poses operational concerns (Ueckerdt, Brecha et al. 2015). They cannot be relied upon to generate power whenever needed. The sun doesn’t shine all day, nor does the wind blow on a continuous basis.

1.1 Problem Statement

Power system infrastructures must, at all time, match supply and demand, at all locations across the network. However, reliably maintaining this balance can become increasingly difficult, considering the growing penetration of renewable energy sources. Two major changes need to be addressed: (1) adjustment in power flow patterns, which could potentially cause grid congestions and/or the need for large grid reinforcement, and (2) increase in variability in power generation, which would likely require balancing through energy storage systems, or increased power trading between different zones (Svendsen and Spro 2016). The question of power system architecture thus becomes critical, in the sense that an inadequate architecture would impede the ability of the system to be reliable, sustainable, and affordable.

More centralized power infrastructure systems, as compared to more decentralized ones, are composed of large scale generating units. Since the largest pools of renewable energy (sun power in Sahara desert, wind on North Sea across European coasts, hydropower in central China…) tend to be the farthest from human population hubs, large-scale transmission networks are needed (Macilwain 2010). The argument is to design wide transmission networks in order to carry electricity over long distances, from large scale power plants, primarily renewable. For example, the power generated by the Three Gorges Hydropower Plant in Central China is transported to load centers in the Guangdong province, southeast China, via a 940 km long transmission line (Zhou 2010). This type of architecture would also allow, for instance, large nuclear plants to be built far from human populations, in support to renewables. Large infrastructure systems are designed to provide services in such a manner to strike a balance between possibly conflicting objectives, including economic cost, environmental impact and reliability (Hines, Blumsack et al. 2015). This structure considers energy storage, enables a maximum use of renewable sources, market expansion, but appears more vulnerable, due to its highly interconnected architecture.

On the other hand, more decentralized infrastructure systems would offer improved local reliability (Zerriffi, Dowlatabadi et al. 2007), and present less vulnerability as the level of interconnectedness is fairly low. The falling costs of distributed power generation (EIA 2013), in addition to the growing interest in smart micro-grids, which would provide backup generation (Kahrobaeian and Mohamed 2012), help strengthen the argument for this type of architecture. Small infrastructure systems do not require supply lines, and therefore do not incur transmission costs, as situated close to energy consumers and designed to cover local demands (Ackermann, Andersson et al. 2001). Their relatively small sizes offer geographical and operational flexibility, which makes it possible to be set up even in congested areas (Martin 2009). They are also more appropriate for back up sources, which help prevent operational failures in case of network problems. Another argument in favor of this architecture is the substantial technical advances, with new technologies such as micro turbines that are being introduced, and existing ones like reciprocating engines, that are being improved (IEA 2002), making these systems more likely to meet efficiency targets. This structure also considers energy storage, enables a maximum use of renewable sources, but would deter the network's ability to supply power if sources in a certain location cannot respond to local load changes.

The centralized and decentralized options mentioned above are the two extremes in a continuum of architectures, which each have benefits and inconvenient. They are presented here as references and will help better characterize other types along that continuum.

Energy planners have the task of designing an infrastructure power system to provide electricity to population, at a given set of locations. Each location i has some demand, d_i, and (possibly) produce electricity via local generation stations at a production cost, c_i. In order to satisfy the demand at that location, there are options of either produce locally at a cost of c_i, or build an interconnection to another location at a cost c_{ij} (cost of interconnection between location i and location j). Deciding the option to take will have serious implications given that the power system reliability and the future shape of that system are at stake. These implications may yield deeper insight into complex issues, namely expansion of power system infrastructure, or its potential transformation over time. What type of architecture is needed, if the objectives are, not only to minimize costs, but also minimize environmental effects and maximize reliability? This issue is even more pressing now that nations across the globe are heavily investing in the use of renewable sources to match the rising demands (IEA 2014). The substantial increase in use of renewables is therefore not in question (Hillebrand, Buttermann et al. 2006, Blazejczak, Braun et al. 2014). What is, is where and how all this energy, if generated, in complementarity with fossil fueled energy in the network, will be used.

1.2 Motivation

This portion of the dissertation serves two purposes. First, it highlights the need to re-think power system architectures given the growing importance of renewable in electricity generation. Second, it draws on the complexity in energy planning to explain the motivation behind developing a computational model.

1.2.1 Power system architecture and renewable energy

Growing power demand and technological development of new energy sources, mostly renewable, not only put a strain on the existing transmission system (QTR 2015), but also raise questions regarding investments in new transmission lines (Lund and Münster 2003). Hence, there is a need to investigate power system architectures, and assess system performance considering the rising level of penetration of renewable in existing networks. According to Deshmukh and Deshmukh (2008), renewable sources can be integrated into the network, either by a centralized or by a distributed system. Would a more connected power system infrastructure be more appropriate in addressing the energy planning challenge?

Lund and Østergaard (2000) seek to identify circumstances helping to determine the need for transmission capacity in Denmark. In their analysis, the authors compare demands for the electricity grid in terms of worst-case situations with two different types of grid designs. One type consists in the current design (mixture of overhead 400 and 150 kV transmission lines), and the other one, consists in a replacement of all 400 kV by 150 kV. The situations considered are determined by the size of demand, the structure of energy supply, the regulation strategies, and the amount of renewable sources. The analysis is conducted using ELNET, which is a general load flow model. As a result, the authors were able to identify strategies which were more likely to be successfully implemented in either power grid architecture type.

In a later study, Lund and Clark (2002) discuss and analyze two different national strategies in Denmark for tackling the issue of fluctuations in electricity production due to renewables. One strategy, the export strategy, proposes to sell and buy electricity with surrounding countries, while the self-supply strategy, proposes local generating units to meet both demands. The authors highlight the challenges into choosing appropriate energy-production system designs to implement both strategies.

Alberg Østergaard (2003) looks into the gradual transition from large power plants to many small and geographically scattered CHP (Combined Heat and Power) and wind-power plants, still in Denmark. In this work, the author analyzes the requirements of the transmission grid in (1) a year 2020 situation with power balancing as it is now, with large power plants, and (2) a year 2020 situation with geographically-scattered power balancing. Scenarios are run via the EnergyPlan model, which calculates aggregated hourly consumption and power production on various types of units. The scenarios are mainly based on changes in values of productions and consumption, that is, CHP production, wind power production and consumption, respectively, considered either high or low. His study suggests circumstances under which strategies that need to be implemented, in each of the different grids type.

In their study, Liu, Lund et al. (2011) analyze the ability of the existing Chinese energy system to integrate wind power, as well as changes that need to be done to integrate more fluctuating renewable energy in the future. They conduct their analysis, using a model, helping estimate the effects of two parameters: the ability of the system to avoid excess electricity production, and the ability of the system to decrease fuel consumption. The objective is to identify the maximum feasible wind power penetration for the existing energy system. The authors identify the inadequacy in the transmission network, the rigidity of the power supply structure as well as the lack of diversity in regulations of grid stabilization as the main challenges for the development of large-scale wind power. Their result analysis proposes, as a solution, a redesign of regulations to secure grid stability through a more varied mix of energy supply sources, integration of storage units, and the deployment of electric vehicles in order to promote off peak electricity utilization.

Capros, Tasios et al. (2012) present various scenarios examining progressively rising levels of renewable energy sources. In their study, the authors point to system flexibility as a leading factor to increased costs. According to them, while increased system flexibility and back-up generating and storage units are needed to cover variability, installing more renewable resources would result in them being used at a lower capacity factors. Their analysis suggests the enhancement of transmission network when dealing with a low renewable penetration, while a higher penetration would necessitate the deployment of energy storages.

Hui, Xiaozhou et al. (2012) predict the need for a more flexible power system design to deal with increasing uncertainties from renewable energy integration. According to the authors, this integration will require fundamental changes in the way power systems are planned and organized. Their paper looks into flexible transmission network planning, comparing various planning schemes, and assessing investments and reliability.

Mai, Sandor, et al. (2012) are interested in estimating the extent to which renewable energy technologies available today can meet the U.S. electricity demand over the next several decades. Their study revolves around three main questions, addressing the contribution of renewable energy technologies in future U.S. electricity supply, the ability of the existing power system design to handle increasing levels of variable generation, and the appropriate combination of diverse sources which will enable reliability of the system. Key results include the constraints associated with (1) the deployment of renewable energy technologies, adequacy in grid operability and hourly resource, and (2) transmission expansion and costs, and (3) environmental implications of high renewable electricity futures.

Zhang (2013) claims that the push for smart grids and the increasing penetration of renewable energy resources today has significantly influenced operations and planning of the existing power system. The power grid network in the future is expected to be smarter, flexible and robust enough to withstand uncertainties and disturbances. With these changes come some problems. The author cites (1) the load increase, which may change the power flow and result in potential overloads and violate reliability criteria, and (2) the locations of renewable resources, as being located in remote areas and not readily connected to the main power grid. His research analyzes the changes in the transmission network that will be needed to address those issues.

IRENA (2015) supports that high shares of renewable energy sources require a re-thinking of the design, operation and planning of future power systems, both at the technical and economic levels. A system of that sort would require more flexibility, due to the intermittence of the renewable sources. According to the authors, the integration of a significant amount of renewables into existing power grids requires substantial changes to ensure reliability, sustainability, and cost effectiveness. Changes mentioned in the study include (1) allowing electricity flow, in both decentralized and centralized designs, and their integration, (2) developing smart grid and demand management mechanisms in an effort to increase flexibility and responsiveness and smoothing out peak-loads, (3) improving grid transmission system, aimed at increasing balancing capabilities, flexibility, stability and security of supply and (4) establishing storage units.

On the basis of these studies, we can see that the rising demands and mounting levels of penetration of renewable sources in the grid pose a serious problem in terms of the ability of the power grid to sustainably, reliably, and cost-effectively match the demands (Lund 2007). The use of renewable sources undeniably presents great advantages, but poses new challenges as well (Lilienthal and Power 2007, Narodoslawsky, Niederl-Schmidinger et al. 2008, Navid and Rosenwald 2012, Maier and Gemenetzi 2014). These challenges are addressed at the economic, policy, technology and environmental levels (Coll-Mayor, Paget et al. 2007, Hammons 2008, Bayod-Rújula 2009, Brand and Zingerle 2011, Hand, Baldwin et al. 2012, Blarke and Jenkins 2013). However, no study explicitly addresses these challenges at the architectural level. The importance of analysis at this level is critical, as it enables further understanding of the complexity of the grid systems, which would help design and manage them.

What do we mean by Power system architecture?

Garlan and Perry (1995) define a system architecture as "*the structure of components, their interrelationships, and the principles and guidelines governing their design and evolution over time."* In our case, the power system architecture refers thus to how components in that system connect and function together. In this system, electricity is supplied through generators, carried from generation centers to loads through a transmission system, and delivered to users through a distribution system. Supply may be matched to demand either via a transmission grid and local distribution networks, or directly via local distribution networks, and through centrally or de-centrally administered market trading and balancing arrangements (Zhang et al., 2018). Here, market trading is a system which allows purchases, through bids/offers to buy/sell electricity (Dempsey, 2011). It is therefore a critical part in grid architecture analysis since it constrains imports/exports, and ultimately impacts on the grid reliability.

Looking at the challenges posed by a high share of renewable energy on the power grid at the architectural level thus means looking at how structured the system is. Say a power grid system is composed of several zones, linked via transmission lines. By structure, we mean (1) how connected or fractured the grid is, (2) how clustered the grid is, and (3) how centralized the whole system is. Centralized structures imply that supply and demand are matched via a transmission and local distribution system networks and through a centrally controlled power trading arrangements (IET 2016), while decentralized ones imply that supply and demand are matched directly, via distribution system networks and through locally power sharing arrangements (Ackermann, Andersson et al. 2001).

What is missing is an analysis of power system architectures, considering not only transmission lines, but also supply scale and location, and market trading and how these factors influence the grid performance, in terms of sustainability, affordability and reliability. This is the aim of this thesis. Table 1 displays a summary of studies addressing challenges to face in the integration of renewable sources.

Table 1: Summary of studies addressing challenges linked to renewable integration

	Economic	Policy	Technology	Architecture		
				Transmission Lines	Supply scale/location	Power Market trading
Liu, Lund et al. (2011)		×				
Brand and Zingerle 2011	×			×		
Capros, Tasios et al. (2012)	×	×				
NREL (2012)	×	×	×	×	×	
Mai, Sandor et al. (2012)	×	×	×			
Zhang (2013)			×	×		
Blarke and Jenkins 2013	×	×	×			
Castillo and Gayne (2014)	×	×	×			×
Vincent and Yusuf (2014)		×	×	×		
Mai, Hand et al. (2014)			×	×		
Weitemeyer, Stefan et al. (2015)			×		×	
Jacobson, Delucchi et al. (2015)			×		×	
Lantz, Mai et al. (2016)	×				×	×
Jacobson, Delucchi et al. (2016)	×	×	×		×	

1.2.2 Motivation for modeling the power system

The Merriam-Webster dictionary defines “planning” as “*the act or process of making or carrying out plans…*” To “plan” is defined as to “*decide on and arrange in advance.*” The notion of planning thus suggests the idea of preparation ahead of time, or anticipation of something that is suspected or thought to happen in the future.

In our case, energy planning refers therefore to preparation of the energy system for meeting the demands in a sustainable manner. The development of sustainable energy systems has been at the forefront of priorities in recent years given the predicted increase in demands. Indeed, the population size is growing, as is material and energy consumption, which leads to an ever-increasing environmental impact (Nikolić 2010). According to Jebaraj and Iniyan (2006), it is clear that this rise in energy consumption can no longer be satisfied by the traditional inefficient energy technology using a few local resources. Moving toward sustainable energy systems will thus require not only cleaner and more efficient energy supply, but also power infrastructure networks that are conducive of such objective.

The difficulty that arises is the ability to anticipate or, say, accurately anticipate changes that might occur in the future. Those changes may take place at various levels, namely prices (how will fuel price evolve with time?), electricity demands, technology (how technology in electricity production, transmission, etc. will evolve with time?), regulations, etc. Energy planning helps answer four questions: What? Where? When? How much? What actions need to be taken? When are actions needed? Where to implement actions? How much should be done? This planning is implemented at four levels: generators, storage units, transmissions and operations. The 1st three cited are similar in principle. The objective is to determine what generating unit should be expanded/built in terms of capacity, where this expansion/construction should take place, when and how much power should be added. The same principle applies to storage units and transmission lines. This type of planning is rather long term. The operational planning is instead short term, with day-to-day activities required to run the power system. In this case, the activities involve deciding what generating unit to dispatch, where to dispatch it, when and how much of its capacity to use. The uncertainty surrounding these aspects requires a near perfect or satisfactory understanding of the actual functioning of the energy system, in order to perform adequate planning.

One way to acquire this understanding is to build a model of a power system. A model is a simplified representation of the real system, specified in space and time (Phan and Butler 2008). A real system is, very simplistically put, a complex phenomenon or mechanism in the real world; here, a power system. A model should, not only be an accurate approximation of the real system (realistic in the sense that the level of abstraction should not lead the model not to incorporate or integrate the system's salient features and key components) but also be not so complicated (simplistic in the sense that the level of abstraction should lead the model to smartly reduce the real system complexity) that it would impair the ability to understand it (Maria 1997). It soundly shows the connectivity between the key elements and captures critical phenomena taking place in the real system. Once created, the model needs to be simulated. Simulation is the operation of the model as time evolves (Banks, Carson et al. 2001). Simulating the model would help analyze its behavior through experiments and reach some understanding. Simulation thus puts the model in motion and brings about learning. It mimics the real system, which is continuously changing. It displays the variations of the state of the model's variables over time and ultimately evaluates the performance of the system under different configurations (Maria 1997). Simulation is, therefore, a means to observe and perceive how the behavioral trends of the model unfold. This perception would constitute inference as to the properties of the behavior of the real system. Upon simulation, we may come to a fairly well thought-out and credible hypothesis as to how the system operates. For example, if there is that much penetration of renewable, this will happen. Even then, we cannot be certain, as unexpected changes to the model might occur —a generating unit is broken, a solar plant is not producing nearly as much power as expected, etc. What can the decision makers do to manage these unforeseen events? Create a number of simulations or iterations of the model would allow to ascertain the "what if" situations. That way, decision makers can make well-informed decisions about needed actions to meet the electricity demand.

Energy system models have become the main supporting tool for energy policy (Jebaraj and Iniyan 2006, Bhattacharyya and Timilsina 2010), enabling decision makers to observe the implications of actions taken. The use of energy models dates as far back as in the 70s, with studies analyzing the energy system design based on demand patterns, demand-supply interactions, energy and environment interactions, energy-economy interactions and energy system planning (Subhes and Govinda 2010). A wide variety of techno-economic models were designed, as a response to the oil crisis (Herbst, Toro et al. 2012), to examine the options of alternative energy sources. Several reviews have been made, presenting models used to address energy system issues. In his review, Markandya (1990) focuses on electricity system planning models, and assesses their ability, if any, to capture environmental concerns. Nakata (2004) presents energy-environment models. Connolly, Lund, et al. (2010) review different computer models that can be used to analyze the penetration of renewable energy sources in resource mix. Bhattacharyya and Timilsina (2010) propose a systematic comparative overview of several notorious energy models, assessing their characteristics and the extent to which they capture the features of the energy sector of developing countries. The use of models has helped cover a wide range of issues, namely integration of wind and solar into the grid at high levels of penetration (Zavadil, King et al. 2004, DOE 2008, Mills, Ahlstrom et al. 2009, DOE 2012), market equilibrium for energy supply and demand (Macal, Thimmapuram et al. 2014, Capros, Tasios et al. 2017), electricity production costs (Nassar and Gruber 1983, Valenzuela and Mazumdar 2000, Liu, Wang et al. 2012), capacity expansion of generators, transmission lines and storage units (Logan, Sullivan et al. 2009, Mai, Drury et al. 2013, Aghaei, Amjady et al. 2014, Zinaman, Mai et al. 2014, Blair, Zhou et al. 2015, Hale, Stoll et al. 2017), etc. The intensive use of models in this area demonstrates not only the adequacy of models to answer questions related to energy planning, but also the trust placed in them by energy planners and decision makers. Energy models are used as a basis for investment plans, legislation and even regulations (Unger 2010). For instance, NEMS, the model developed and maintained by the US Department of Energy, is used to project over several decades the energy, economic, environmental, and security impacts of energy policies and assumption about macro-economic and financial factors in the United States (EIA 2009). Likewise, METIS is a model used by the European Commission to further support its evidence-based policy making, for electricity and gas (ARTELYS 2016).

Using a model is an appropriate approach to answer our research question. This choice is justified, as explained earlier, by the (1) ability of models to provide insights into how energy systems function and may evolve in the years to come, which is critical for efficient planning, and (2) the documented exclusive resort to models by researchers and decision makers to address energy system issues.

1.3 Research Objective

As the concern for a more sustainable future is consistently growing, the issue of how to efficiently and effectively design power systems has drawn even more focus. This research is based on the premise that there is a need and a lack of works tackling the problem of analyzing types of system architectures that will best balance costs, environmental concerns, and reliability objectives. Therefore, we set the research objective as following:

To explore associations between types of power grid architectures and their performance, in terms of sustainability, affordability, and reliability.

1.4 Research Question

Given the research objectives and the previous discussion, the central research question could be formulated as: *Which architecture type of power grid infrastructure offers best performances in reliability, sustainability, and affordability?* However, it is important to add some context. Given the fact that power systems architectures have different characteristics from location to location, the question formulated above, we suspect, cannot be answered; at least, not accurately. Different regions have different policies, economic and consumption profiles, weather variables, and technology growth, which guide and help sustain their power systems structure. These systems are thus subject to different conditions and constrained to evolve within the boundaries of these conditions. It is therefore necessary to restrict our research question in order to reflect these differences. A more adequate question can be formulated as such: *Given geographic context, which architecture type of power system offer best performances in reliability, sustainability, and affordability?*

Two sub-questions can be derived from the central research question:

- *How can we best capture, in a model, the characteristics of a power system infrastructure, with a diverse mix of energy sources and high renewable energy source?*
- *What is the impact of power system architecture, with high levels of renewable penetration, on economic, environmental and reliability performances?*

1.5 Research Framework

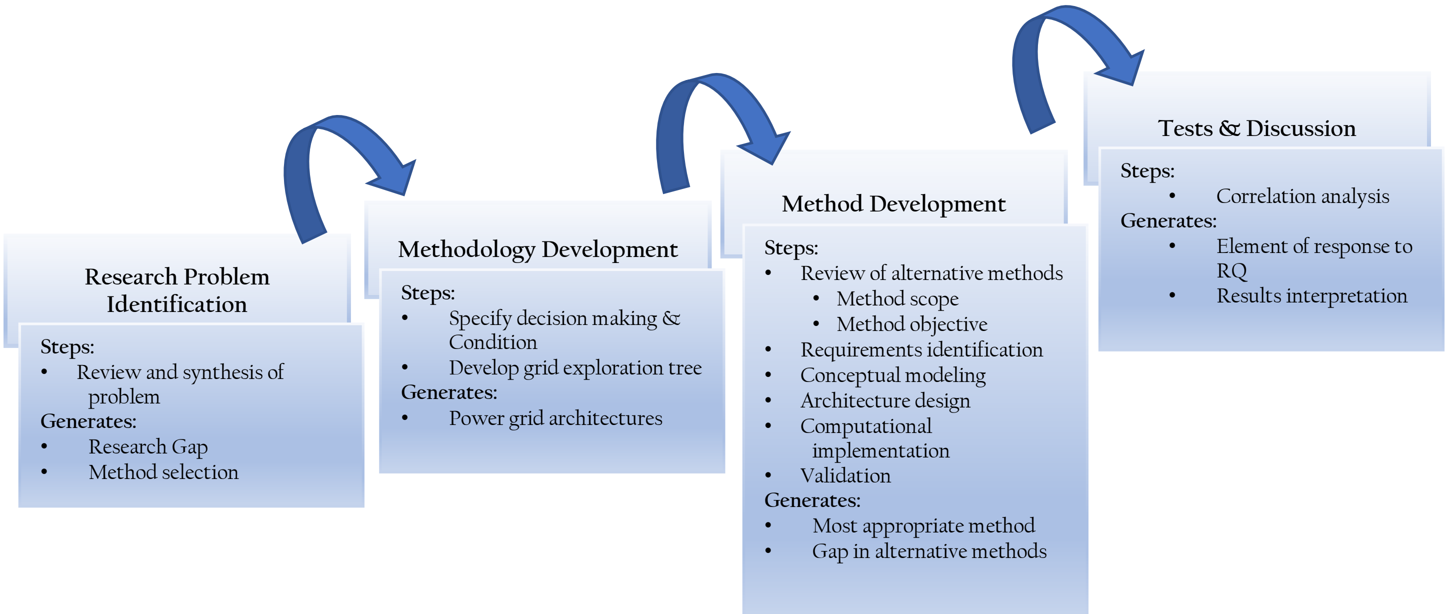


Figure 1: Overview of the methodology framework

Figure 1 provides a broad overview of the methodology applied in this research.

Step1: Problem Identification. This first step consists in the review of the work performed in this area. In that phase, we elaborate on the research problem, formulating the research objective and question. We identify the gap, which we will attempt to bridge. We also identify the method that fits best our need, in that regard.

Step 2: Methodology Development. This second step explains how we intend to answer our research question. In this phase, we present steps that need to be taken, tests to be run as well as metrics to be used to perform our study.

Step 3: Method Development. This third step is the specification and definition of requirements of the method selected. In this phase, we conduct a review of similar methods, in order to assess how they fit to the requirements of our study. We identify weaknesses in alternative methods and present a new one, which is more adapted.

Step 4: Discussion & Implication. The last step consists in performing tests and providing discussion. At that point, we are looking at situating our results in this field of research and assess how they (1) answer our research question and (2) contribute to new knowledge.

1.6 Research Contribution

One of the contributions of this research is to fill the gap in the existing body of knowledge of *large-scale power grid architectures for renewables penetration*. To our knowledge, no work has addressed all critical architectural aspects necessary to handle renewable integration in the grid together. To achieve that, a method is proposed to generate grids of different architectures and explore their relationship with specific performances. This study provides good insight to help decision makers regarding design choices to make if power grids are to perform in a certain way.

The other contribution is the model used in this study. The model built simulates the electricity grid network to determine costs, emissions, and reliability of supply, at various locations in the network. Unlike other energy models, the one developed here is detailed enough to capture architectural features of the grid and technical constraints of the systems components, yet abstract enough to enable a reasonably fast execution. In addition, it addresses incompatibility issues between structures of existing models thus enabling long-term projections validation via system operations and response on the short-term.

1.7 Research Scope

In this section, we lay out the boundaries of our study. We present the overall assumptions made and position the research in its appropriate context.

First of all, let's clarify what we mean by electrical power systems. As stated earlier, such a system is a set of components interconnected together to supply, transport, distribute and use electricity. We are only interested here in the components able to carry out these activities. The system we look at here is thus defined at the activity level. The focus is on the power plants, demand types and quantity, transmission and distribution systems and storage units, how they function individually and collectively, and how their functions contribute to fulfilling the goal of the power system. This is different from other power system models which capture the actual electrical components. We consider those models at a lower abstraction than ours, and therefore not covered in this research. The components referred to are resistors, capacitors, inductors, washing machines, etc., which contribute to the activities cited above but are not directly responsible for performing those activities. Our model would therefore focus on activity development to implement strategies. In our case, these strategies are plans or actions in an attempt to ensure reliability, sustainability and affordability in the system.

Second, we need to frame our study, clearly stating the assumptions and explaining the circumstances under which this research reaches its full potential meaning. We build on the premise supported by the DOE, that a grid should be affordable, sustainable and reliable. It is important to specify what these notions fit in our study.

Reliability: In the words of Endrenyi (1978), "*Reliability is the probability of a device or system performing its function adequately, for the period of time intended, under the operating conditions intended*." Under these terms, the reliability of a power grid is thus related to the probability of delivering electricity to customers in an uninterrupted manner. Three questions arise: How much power is needed? Where is it needed? When is it needed? In this study, we will consider the grid 100% reliable if the amount of power requested by demand is fully met. It reasonably implies that electricity was delivered where and when it was needed, and in the appropriate quantity. Saying that, for example, the level of reliability of a grid is 50% would mean that, in average in the whole network, half of the quantity of power needed was actually covered.

Sustainability: Brundtland (1987) defines sustainability as "*meeting the needs of the present without compromising the needs and opportunities of future generations*". The question of sustainability arises as we need to know how the provision of electricity today will affect the provision of electricity in years to come. It seems clear now, due to global demographic, ecological, economic and geopolitical trends, that the energy consumption has significantly risen, straining conventional resources in their capacity (Kraay 1996). A sustainable system would require therefore, a transition toward the use of renewable resources. That is, resources that (1) would not be substantially depleted due to continued use, (2) would not emit substantial hazards to the environment and (3) would not involve the perpetuation of substantial health hazards (Lantsberg 2005). In our study, we look at sustainability of a power system in term of the amount of harmful pollutants emitted in the electricity generation process. The less emissions, the more sustainable the grid is, as it implies a low-level use of fossil fuels and high-level use of renewables.

Affordability: Generating, transporting, and distributing electricity come at a cost. The different technologies employed - that is, coal, solar, wind, etc. for power generation - offer different ranges of costs. A nuclear power plant for example would necessitate operating costs, but also fuel costs. This would be different from, for instance, a solar plant, which would only require operating costs. Energy trading is also an important factor as power is exchanged (imported or exported) throughout the network if it is the least expensive option. In our study, we look at affordability of a power system in term of the total profit made, considering revenues and total costs, including operating and maintenance costs, overnight costs, and market trading costs.

CHAPTER 2

BACKGROUND OF THE STUDY

This section provides a survey of past research relevant to this dissertation. It begins with a review of energy system models, with their descriptions and objectives, and is followed by another review of power system models. It ends with the definition of the gap that we intend to fill.

2.1 Energy System models

A wide range of energy models is used by various researchers to evaluate energy policies. Prevalent models are MARKAL (Suganthi and Samuel 2012), TIMES (Loulou and Labriet 2008), MESSAGE (Fishbone and Abilock 1981), NEMS (EIA 2009), PRIMES (E3MLab 2013) and LEAP (Heaps 2008).

MARKAL (MARKet ALlocation) was developed as a collaborative effort through the Energy Technology Systems Analysis Programme sponsored by the International Energy Agency (IEA) which started in 1978 (Tosato 2008). Its main purpose is to assess the possible evolution of an energy system, considering associated economic and environmental issues at the global, multi-regional, national, state/province or community levels (Mahmud and Town 2016). This model has been used in several studies, including the role of nuclear energy in long-term climate scenarios (Vaillancourt, Labriet et al. 2008), the impacts of wind power on the future use of fuels (Nguyen 2007) or the effects of integrated policies on the use of renewable sources, climate change mitigation, and energy efficiency improvement (Giannakis 2007).

TIMES (The Integrated MARKALEFOM System), which later on evolved into TIAM (TIMES Integrated Assessment Model) was developed under the Energy Technology Systems

Analysis Program (ETSAP), and is an upgrade of MARKAL (Loulou, Goldstein et al. 2004). The model is mainly used to determine the energy system that would meet the energy demands over the entire time horizon in the cheapest way possible (Loulou, Remne et al. 2005). MARKAL and TIMES share similarities in terms of modeling paradigm, technology considered, and dynamic partial equilibrium energy markets (ETSAP 2008). However, many dissimilarities are observed, namely in process generality and flexibility, investment and dismantling lead-times and costs, commodity related variables, and climate equations (ETSAP 2008).

MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) has been developed by the International Institute for Applied Systems Analysis (IIASA) in Austria since the 1980s (Messner and Strubegger 1995). The model principal objective is the planning of medium to long-term energy-systems, analyzing climate change policies, and developing scenarios for national or global regions (Connolly, Lund et al. 2010). It is also used to help inform in GHG emission limitation and reduction measures. This model has been used in studies looking into sustainable energy plan design (IAEA 2008), scenario assessment with emphasis on climate stabilization (Riahi, Grübler et al. 2007), and policy options for renewable energy use (IAEA 2007).

NEMS (National Energy Modelling System) is a model created by the U.S. Department of Energy, Energy Information Administration (EIA), which simulates the behavior of energy markets as well as their interactions with the economy in the US, on yearly basis (EIA 2009). Its main purpose is to help develop the Annual Energy Outlook, which consists in providing projections of domestic energy markets, taking into consideration different assumptions of macroeconomic growth, fuel prices, technological evolution, and energy policies (EIA 2017). The model has been involved in numerous studies, namely evaluation of the future of coal-fired power plants in the U.S. (Geisbrecht and Dipietro 2009), the impact of carbon reduction policies on the electricity sector (Hadley and Short 2001), or impacts of renewables on energy markets in the U.S. (Hadley and Short 2001).

PRIMES provides detailed projections of energy demand, supply, prices and investment in the entire energy system, also including gas emissions (E3MLab 2013). The model is a comprehensive energy demand and supply model which simulates a market equilibrium solution for energy supply and demand (E3MLab 2007). PRIMES has previously been used to create energy outlooks (Capros, Mantzos et al. 2008), design climate change and renewable energy policies (CEC 2008) as well as analysis policies in an effort to lower emissions (Bulteel, Belmans et al. 2007).

LEAP (Long-range Energy Alternatives Planning) is an integrated model developed by the Stockholm Environment Institute to assist in energy policy (SEI 2012). The model is used to monitor energy consumption, production, greenhouse gas emission as well as resource extraction in all sectors of the economy in an effort to assess energy policy and climate change mitigation (SEI 2012). This tool has been previously used in research, aiming to analyze reduction in energy consumption and gas emissions within road transportation (Yan and Crookes 2009), and analyze implications of penetration of renewable energy (Giatrakos, Tsoutsos et al. 2009).

Caution, however, needs to be observed when it comes to the use of energy models. Although energy models are mainly used to answer energy planning questions, these types of models are not appropriate for power grid simulation. Energy system models capture the behavior of the entire energy system and its impact on the wider economy over a medium and long-term horizon. With regard to the "entire energy system," the combination of the electricity sector, the heat, gas, mobility, and other sectors as appropriate should be understood (Abrell &

Weigt, 2012). In these models, the power sector is endogenous and controlled by the combined behaviors of supply sectors and end-use sectors driven by exogenous demands (Deane, Chiodi, Gargiulo, & Ó Gallachóir, 2012). The electricity sector is thus coarsely represented, with no regard for reliability, flexibility, and unit commitment and dispatch. These limitations hamper their ability to provide trusted results regarding power system planning. By contrast, power system models focus only on the electrical power system (supply, transport, and use of electricity). Electricity (or power) is a specific form of energy and is the main form we are interested in.

The difference between energy and power system models resides in their focus and the questions they are answering or in application. Energy system models tend to cover a much broader range of problems, for instance, linkages between energy and the economy (Messner and Schrattenholzer 2000, Nakata, Silva et al. 2011) or optimal long-term energy supply strategy based on cost minimizing (Hainoun, Seif Aldin et al. 2010) among others. Power systems are literally and exclusively focused on electricity supply, demand, and transmission. These models are thus more appropriate for power system planning both in the short and long terms. They represent the power sector in a more detailed manner, and have more propensities to capture phenomenon critical to that sector.

2.2 Power System Models

We categorize power system models into three groups, namely power flow models (Milano 2010, Preece 2013), capacity expansion models - e.g. RPM (Mai, Drury et al. 2013), WASP (IAEA 2001), ReEDS (Short, Sullivan et al. 2011), EMCAS (Veselka, Boyd et al. 2002) and SWITCH (Fripp 2012) - and production costs models - e.g. PLEXOS (CAISO 2010), GridView (Feng, Tang et al. 2002), WILMAR Planning Tool (Larsen 2006) and GE MAPS (GE Energy 2010).

Power flow models help simulate the transmission network, looking to find optimal conditions of functioning of physical components (resistor, conductor, capacitor, etc.). These models are mainly used to address power flow issues, namely frequency and stability and voltage control. These models look at power system in terms of network of electrical components (capacitor, resistor, inductance, etc.) or appliances (refrigerator, dish washer, washing machines, etc.), describing their physical behavior. Their main objective is to specify optimal operating limits of the electrical components. These models remain at the technical level and are not within the scope of our study. By power system, we mean network of entities interacting with one another to enable supply, transport, distribution, and use of electricity. In that sense, the models we are interested in would represent elements or components able to perform these activities. Unlike power flow models, our models of interest would rank at the activity level, with the focus on activity development to implement strategies. In our case, these strategies are plans or actions in an attempt to ensure security, sustainability, and affordability in the system.

Production costs models (PCM) help simulate operations of power systems, namely security-constrained unit-commitment and security-constrained economic dispatch, market analysis, transmission analysis and planning, considering economic, environmental and operational constraints (Stoll, Brinkman et al. 2016). The models analyze conditions which would allow least costly dispatch of energy sources. Typical outputs include hourly generating unit usage, locational marginal prices, emissions, etc.

WILMAR (Wind Power Integration in Liberalized Electricity Markets) was developed by RISØ National Laboratory in a collaboration with other partners in the EU-funded WILMAR project (Holttinen, Uhlen et al. 2005). The main objectives of the model are to investigate (1) the issue of system stability given the wind integration and (2) the technical and cost issues of integrating large amounts of wind power into the electricity system (Foley, Gallachóir et al. 2010). WILMAR has previously been used to analyze the dynamics of operation costs due to increased wind-penetrations (Meibom, Weber et al. 2009), identify the consequences of increased wind power (Meibom, Barth et al. 2008), and assess the effects of wind intermittency and load variation on the dispatch of power systems with high wind-penetrations (Tuohy, Meibom et al. 2009).

PLEXOS was developed to model electricity markets, with features enabling electricity Price Forecasting, transmission asset valuation as well as market analysis and design (Papadopoulos and Valdebenito 2015). The model suggests ways to optimize electricity and natural gas sector investment and operations, taking into account operational limitations as well as storage management. Previous research using this model includes, among others, the impact analysis of offshore wind forecasting error on electricity markets (Higgins and Foley 2013), the economic evaluation of distributed energy systems (William E, Luke J et al. 2012), and the effects of storage on solar and wind sources intermittence (Wright 2016).

GridView is a power market simulation model, the main goal of which is to combine system power details - namely transmission model, and supply and demand model - with market and economic aspects. The model allows market scenarios to be tested and to perform market analysis (energy market price, market performance benchmark, etc.), generation (generation portfolio optimization, generation plant performance and efficiency, etc.), and transmission (transmission asset utilization monitoring, transmission bottleneck identification, transmission congestion assessment studies, etc.) (ABB 2005). GridView has previously been used to perform economic evaluation of congestion in transmission system (Feng, Pan et al. 2003)

GE MAPS (Multi-Area Production Simulation) models the economic operations of a power system. The model integrates highly detailed representations of load, generation, and transmission systems into a single simulation platform, helping to assess the value of generating assets or identify costly transmission bottlenecks (GE Energy Consulting 2013). Previous research using GE MAPS includes the evaluation of power system economics and impact of congestion, high wind penetration and standard market design, etc. (Zandt 2010).

PROMOD is an integrated power generation and transmission market simulation tool that presents extensive details in generating units and their operating characteristics and constraints, transmission lines and constraints, generation analysis, and market system operations (Lohmann 2015). The model captures all the costs of operating a fleet of generators, including startup, shutdown, O&M and fuel costs, calculates locational market prices, and performs hourly chronological security constrained economic dispatch and unit commitment, while considering operating constraints (ABB 2015).

Capacity expansion models (CEM) help simulate generation and transmission capacity investment, considering scenarios about future power demand, fuel prices, technology cost, and performance (Blair, Zhou et al. 2015). These models help answer questions related to the transmission or mix of generators capacity to build in order to match future loads. Typical outputs include generation and transmission capacity expansions or retirements, annual generation, etc.

The WASP (Wien Automatic System Planning Package) was created by the Tennessee Valley Authority and Oakridge National Laboratory, with the principal objective to design an optimal expansion plan for a power generating system over a long period, considering constraints (IAEA 2001). The optimum expansion plan is defined based on (minimum total) costs, including capital investment costs, fuel costs, operation and maintenance costs, fuel inventory costs and cost of energy demand not served (Rogner, Langlois et al. 2004). WASP has previously been used to evaluate the potential of biomass power generation (Santisirisomboon, Limmeechokchai et al. 2001) and the future role of nuclear power (Lee and Jung 2008).

EMCAS (Electricity Market Complex Adaptive System) was developed by Argonne National Laboratory to simulate the operation of the power system (ANL 2008). EMCAS is used to study restructuring issues in the electricity market, with markets actors including generation companies, transmission companies, distribution companies, demand companies, independent system operators (ISO) or regional transmission organizations (RTO), and regulators (Macal, Thimmapuram et al. 2014). The model is mainly used to perform market analysis and identify alternative company strategies and associated risks. In past research, the model was used to study market competitiveness (Cirillo, Thimmapuram et al. 2006) and also conduct short-term electricity market analysis (Thimmapuram, Veselka et al. 2008).

Short, Sullivan, et al. (2011) present the ReEDS (Regional Energy Deployment System), which analyzes expansion plans for electricity-generating, transmission, and electrical storage technologies, addressing cost of transmission, variability of renewable resources as well as their impacts on the reliability of the electrical grid. The model is mainly used for addressing the electricity market issues that have the most influence on renewable energy technologies. ReEDS seeks to minimize both capital and operating costs for the U.S. electric sector, namely costs of (1) adding new generation, storage, and transmission capacity and (2) operation and maintenance for all existing capacities.

Fripp (2012) present the SWITCH model, which analyzes capacity (generators, transmissions and storage) expansion conditions in a power system in order to meet electricity demands at the lowest cost over a long-term period. The model assists in decisions regarding (1) addition in generation capacity at different locations, power transfer capability between these locations and (2) operation of existing generation capacity. SWITCH also makes hourly decisions about how much power to generate from each dispatchable power plant, store or transfer along each transmission route. The model is adequate to analyze scenarios with high penetration of renewables and is used to determine optimal portfolios of renewable and conventional resources for deployment in large-scale power systems.

Mai, Drury, et al. (2013) present the Resource Planning model (RPM) used for mid- to long-term scenario planning of regional power systems. The model is designed to evaluate scenarios of penetration of renewable technology in an effort to meet renewable portfolio standard (RPS), and also to estimate circumstances under which system expansions are possible. Expansion decisions are made at three levels, namely capacity, transmission, and storage (determination of the types and sizes of generators, transmission lines and storage, respectively, to build in each region). Besides being a power system planning tool, RPM also implements hourly dispatch for existing generators, hourly power flow between regions and hourly charging, discharging and spinning reserve provisions.

With little doubt, CEM are the preferred type of models to analyze possible future paths for power systems, identify most efficient and environmentally friendly way for power systems development, and assess feasibility and consequences of policies taken along the way. However, because of their structure and granularity level, they do not capture chronological unit commitment and unit dispatch, but rather use aggregate model plants, mostly at a zonal levels (state, regional, and national), offering high-level long-term (yearly or multi-year basis) view of the evolution of power systems. Similarly, PCM structure and level of granularity do not allow them to answer questions relative to long-term investment in new generation or transmission capacity. Instead, they capture detailed grid operations and offer short-term solutions to production cost minimization.

These models differ in terms of time scale and level of granularity, which makes it virtually impossible to verify long-term projections applicability in the short term. CEM high-level projections need to be validated, through power system operations in the short term. Although long-term planning helps shape the grid architecture (generation fleet and transmission and distribution networks), daily grid operations, in return, help (re)adjust long-term planning. It is critical to examine the detailed system response to the various suggested projections, as it helps attest to the viability and soundness of these projections. This need is even more relevant for power grids in developing nations and their low reliability. How can we reconcile long-term planning with short-term grid operations?

Though PCM and CEM could be used in tandem, this procedure may require several iterations to arrive to optimal solutions (Mai et al., 2013) and considerable computational power, which may be impossible when dealing with large scale power grids and longer planning horizons. To answer this question, Diakov et al., (2015) present a tool attempting to link CEM and PCM. More specifically, the authors focus on taking ReEDS output and translating it into an input database for the PLEXOS production cost model. According to the authors, this tool's main goal is to impose regional generation projections outputted by ReEDS onto detailed, component-by-component, PLEXOS. Despites their efforts, the need is not quite addressed, given the differences in physical and temporal levels of details. Generation expansion projections are not always applicable, plant characteristics and details not always compatible, and transmission expansion completely impossible to implement (Diakov et al., 2015).

Few other models attempt to answer this question. ICF (1994) present the IPM, which is a long-term capacity expansion and production costing model used for analyzing the North American electric power sector. It is a multi-regional, deterministic, dynamic linear programming model that performs system dispatch and operations simulation. Though relevant, the model does not capture the unit commitment problem. In addition, IPM (1) assumes perfect competition and (2) solves ED problem with perfect foresight. Assumption (1) means that the model overlooks any market imperfections such as market power. This is problematic at two levels. First, in a competitive market, sellers look to maximize their profits, and therefore, based on their generation technology, may increase their influence in the market. Second, this assumption is based on the premise that all sellers/buyers have full knowledge about each other bid/offer, which is unrealistic. Assumption (2) implies perfect foreknowledge of future electricity demand, fuel supplies, and other variables, which, in reality, are subject to uncertainty. Hart and Jacobson (2011) propose a model to analyze the carbon emissions associated with high penetrations of renewable energy in the long term. Their model uses deterministic planning, assuming that load can be predicted with no error, guaranteeing a power balance that ensures that the generation equals the load at all time. In addition, the model aggregates all available solar and wind data by location and assumes the same potential in all locations. In their study, Jacobson, Delucchi, Cameron, and Frew (2015) support that the power system can be balanced with 100% penetration of renewables, with only wind, water, and solar resources, by year 2050. Their new grid integration model, LOADMATCH, offers a low cost with no-load-loss solutions to this problem. However, LOADMATCH is not spatially explicit, as it does not capture the transmission network and assumes perfect renewables forecasting. Also, it does not model operational reserves, which are essential in achieving reliability, especially when dealing with intermittent renewable sources.

It is safe to say that the complexity of power systems does not help in modeling such systems. While significant progress has been made in the recent years, further advances in power system modelling are needed, given physical and technological changes imposed by especially high penetrations of renewables, to warrant informed decisions. What is needed is a model, detailed enough to capture key operations of day-to-day grid operations, yet abstract enough to enable fast execution. Such a model would position itself at the meso-scale, with a level of granularity in between the ones of CEM and CPM, and addressing the issue of feasibility of power system operation in the short-term depending on the soundness of long-term expansion planning. *Spark*! offers that. It is a bottom-up discrete-event dynamic system model to simulate the behavior of large-scale power systems, accounting for the variability of renewable energy resources, the thermal constraints of conventional generation resources, geographical information, and transmission network. The model also performs (1) security-constrained unit commitment with a flexible look-ahead period, using an enhanced Priority List method, and (2) economic dispatch. Table 2 shows differences between our model and the models mentioned.

Table 2: Summary of the literature of power system models.

Requirements\ Models	WILMAR	PLEXOS	PROMOD	ReEDS	RPM	SWITCH	LOADMATCH	REMix	IPM	**SPARK**
Thermal constraints				×					×	×
Storage unit modeling		×	×	×	×			×	×	×
Transmission lines/contingencies	×	×	×	×	×	×		×	×	×
Chronological load	×	×	×	×	×	×	×	×		×
Transmission Expansion planning				×	×	×		×	×	×
Generation Expansion planning				×	×	×	×	×	×	×
Reserve margin		×	×	×	×			×	×	×
Network Reliability (AC Power Flow, Dynamics, reactance, etc.)			×							
Stochastic planning	×	×				×				×
Security-constrained Unit commitment		×	×							×
Security-constrained Economic dispatch		×	×						×	×
Market trading	×								×	×
Outage (forced and planned)		×		×	×	×			×	×
Scalability level	Low	Low	Low	Low	Low	Low	Low	Low	High	High

CHAPTER 3

METHODOLOGY

In this section, we present our methodology, that is, the steps as well as the sequence we take to answer our research question. As highlighted in Chapter 1, answering this question comes down to addressing 2 sub-questions: (1) How can we best capture, in a model, the characteristics of a power system infrastructure, with a diverse mix of energy sources and high renewable energy source? (2) What is the impact of power system architecture, on economic, environmental and reliability performances?

To answer the first question, we must develop a modeling framework that not only captures key elements of a power system architecture as well as variability injected by renewables, but also offers fast execution. In Chapter 2, we point to the limitations of existing models in that regard (Table 2) and highlight the need for such a model. For our study, the model should present the following characteristics (see Chapter 4 for more details):

1. *Technology explicit*: captures all power generation technologies and their operational constraints.

2. *Data driven*: presents flexibility and high scalability.

3. *Spatially and temporally detailed*: accounts (1) for components on an individual basis, rather than through aggregation, and (2) for chronological variations in renewable source generation, and in load.

3. *Equipped with stochastic algorithm*: accounts for variability injected by renewables.

To answer the second question, we need to perform a statistical analysis of data that describes different grid architectures and their corresponding performances. The objective of this analysis is to estimate association, if any, through correlation testing, between grid architectures and their performances and draw appropriate conclusions. Two questions arise: (a)How to obtain grids with different structures? and (b) How to measure their performances?

What we are looking for in question (a) are power grids, which are plausible, comparable, functionally identical, and structurally different. There are quite a few real-world high RES power grids throughout the world. Power systems in Tamil Nadu (8070.26 MW), Maharashtra (5630.20 MW) and Gujarat (4430.20 MW) in India (MOSPI 2015), Sayanogorsk (5100 MW) in Khakassia, Russia, West of Sodo (1870 MW), Ethiopia (REN21 2016), North Eastern Germany with wind generation able to reach 30,700 MW (Appunn 2015), California in the US (CAISO 2009), Yunnan province in China (6,400MW) (Economist 2017), Justlin/Funen in Denmark (Ackermann 2012) etc. can be cited as examples. In addition, there are also few existing grids between nations, like the Germany-Austria electricity zone (Porter 2017), the Norway-Netherland electricity grid (Ardelean and Minnebo 2015), the Morocco-Spain connection (IEA 2016), etc.

As it can be seen, those grids are in different regions, which means, they are (1) subject to different weather conditions, and ultimately, different renewable energy sources, as well as different load patterns, (2) of different scales, given the sizes of the area they serve, and (3) subject to different regulations. These differences make those grids poor subjects for our study, considering our research question. Considering them would potentially lead us to erroneous or misleading conclusions. Also, there are very few grids of seemingly the same scale and within the same geographical context that we can use for our analysis. Therefore, to find grids which will be appropriate, we resort to computation. We thus need a mechanism which will automatically generate alternative power grids, with different architectures, and within the same geographical context.

Evolutionary computing is a very popular approach used in generative design and modeling (Eiben and Smith 2003, Ashlock 2006). It encompasses genetic algorithms (Holland 1992), evolution strategies (Schwefel 1994) and genetic programming (O'Reilly 1994), which are methods looking to find the best or optimal solution from a great number of possibilities. In our case, it means that such method would provide the “optimal” grid architecture, with the best performance in sustainability, affordability, and reliability. This is not an adequate option for our study for two reasons. First, this is not what we want in terms of results. We are not interested in finding the best grid architectures; we would rather come up with several plausible grid architectures. Second, real world infrastructure systems are the product of an evolutionary process, highly interconnected and interdependent in nature, with a variety of factors which make them far from optimal, but rather contingent on the system’s history (Hathaway 2000), as suggested by the theory of path dependency. Besides evolutionary computing, methods using pure arbitrariness or random generation are also not a good fit. This is because we may have unrealistic grid architectures generated, which will be of no use in our study. What we need therefore, is a generative method that captures path dependency.

The theory of path dependency supports that decisions faced today depend on historical choices made and past preferences and are constrained by current knowledge (Arthur, Ermoliev et al. 1987, Arthur 1989, Page 2005, Vergne and Durand 2010, Mutizwa 2017). This theory attempts to explain how current situations are contingent on and determined by past situations. Complex engineered systems, like power systems, come about as a result of historical, institutional, and behavioral lock-ins and path-dependent technological development trajectories

(Simmie 2012, Fouquet 2016). Path dependency, Simmie (2012) claims, explains why it is proving so difficult to transition from fossil fuel-based energy systems to the general use of renewable energy. Path dependency is more felt in complex systems, given their high interconnectivity and interdependency, not only in terms of social system or preferences but also other various mechanisms (Meng 2016), with which they evolve. An important component in this co-evolution is uncertainty —unpredictability of the system behavior. Researchers in the past have addressed the issue of uncertainty emanating from interrelations between society and infrastructures (Durango and Madanat 2002, Zhao, Sundararajan et al. 2004, Huang, Vairavamoorthy et al. 2010, Dominguez, Truffer et al. 2011).

Current decision-making on strategic planning is thus made up of outcomes from past choices even though they may no longer be relevant, and several other factors which influence behavior or future changes may be unknown. Decision makers are constrained in their ability to take actions, by (1) a limited, often unreliable, information concerning possible alternatives and their implications, (2) a limited capacity to understand available information, and (3) a limited amount of time, with the expectation of a satisfactory outcome. This is what Simon (1997) refers to as bounded rationality. According to him, decisions are made despite incomplete and/or inaccurate knowledge about the consequences of actions for which results may be perceived to be acceptable rather than optimal.

We propose, thus, a generative method that captures path dependency and decisions subject to bounded-rationality and iteratively creates grid architectures. The generation of alternative grid architectures happens by subjecting an initial grid to a heuristic choice method for decision making over a fixed time horizon. The heuristic method is, therefore, a means to come up with grids with different architectures, deriving from the performance of an initial grid.

The method consists in taking actions meant to alter grid structures over time. These actions are described in Section 3.1.1. Therefore, to answer question (a) asked earlier, we can say that grids with different structures are obtained via the use of a heuristic method by taking different actions based on performances of grids in previous years.

As to question (b), grids performances are obtained via simulation. Grids are simulated, and the results show how they behave. For example, gridA, after being simulated, displays unmet demand of quantity q at location l and at time t. Based on this information, actions are taken (Section 3.1.1.) to remedy this situation, which ultimately results in another grid, with a different structure (with a larger generation plant at different or similar locations, or additional transmission lines, etc.).

Once a good size of data points, describing architecturally different grids and their performance is generated, the statistical analysis (correlation testing) can be performed. Figure 2 displays the interplay between simulation, heuristic and analysis performed.

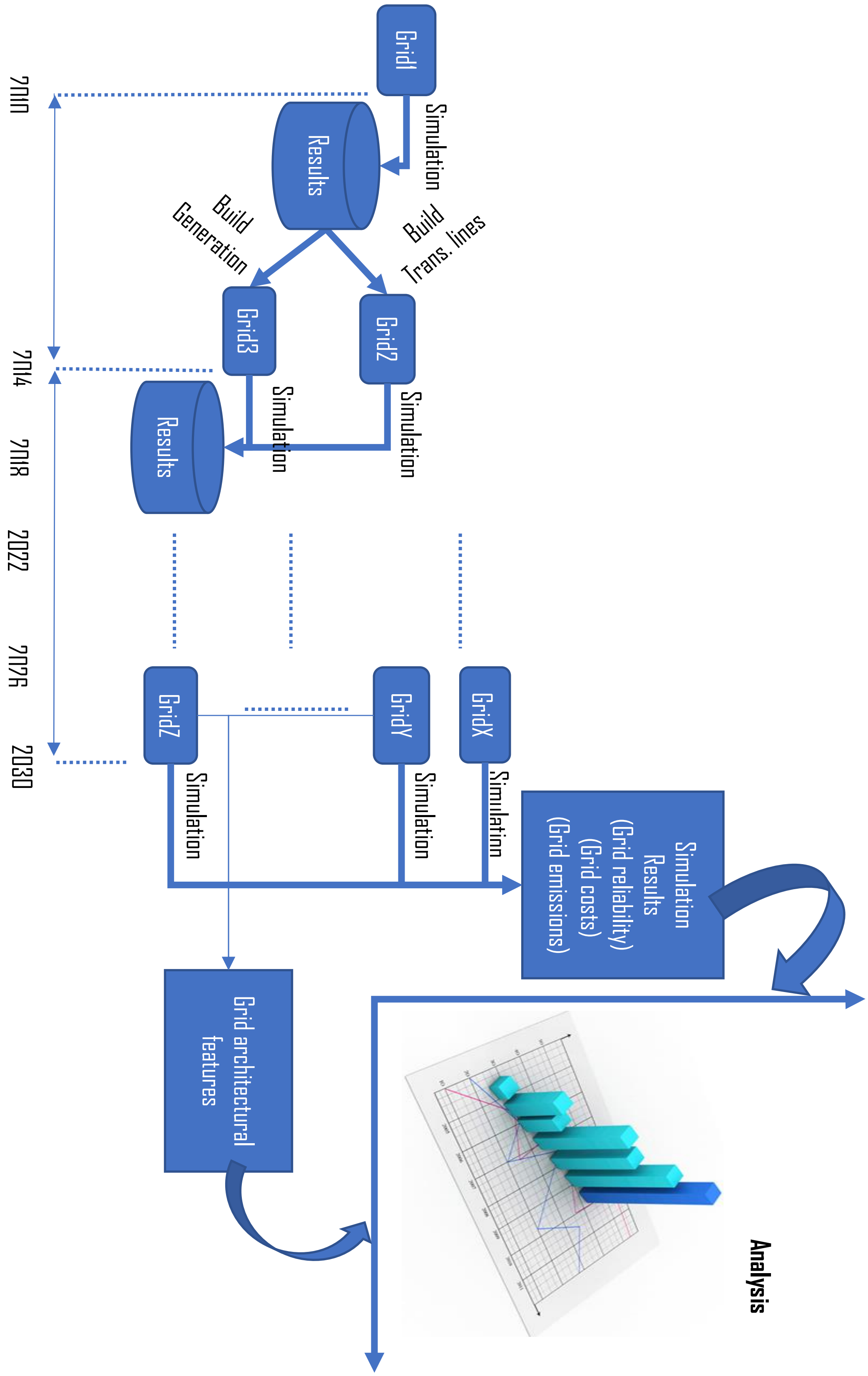


Figure 2: Linking heuristic, simulation and Analysis

As a whole, our methodology consists in four steps: (1) definition of conditions for decision making, in terms of grid modification, (2) development of the grid exploration tree, (3) development of the model, and (4) correlation analysis (Figure 3).

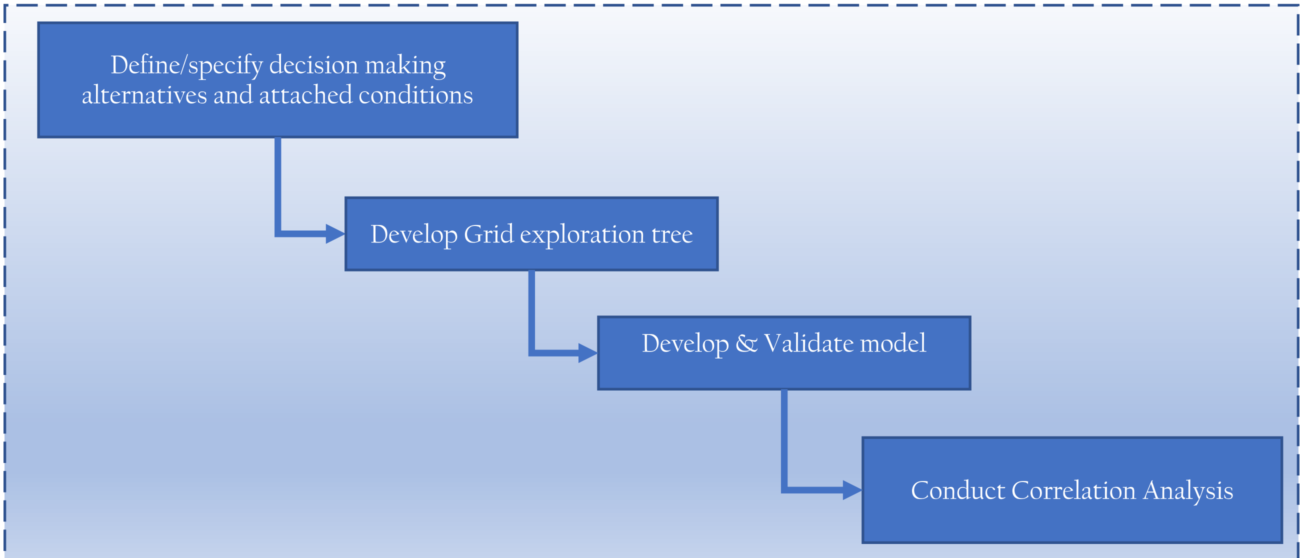


Figure 3: Methodology

3.1 Decision Making, Grid Characterization, and Condition specification

In this section, we describe the process followed to generate various grids. We also specify the different decisions made to alter the grid architecture, as well as the metrics used to characterize the architectures.

3.1.1 Decision making specification

In this section, we define the main decisions to make in order to modify the architecture of the power system. Grids are created following decisions/actions to either build *new generation capacity* in zones or *build new transmission lines* between zones. These two actions are considered because they bring structural change to the architecture. We consider two grids structurally different if one has either a larger or more important transmission network, or has a larger supply scale, or has different a supply location. Each of these decisions branch out, providing an alternative grid. Generations are added based on resource potential in the zone, and are all renewables. Added capacities match the current deficit of electricity while also taking into account the expected demand growth in the future. Two conditions have to be met:

- Conditions to build plants: New units are built when (1) existing units are retired and (2) zones are in deficit, and only in these zones. Also, only renewable source plants can be built.
- Conditions to build transmission lines: New lines are built toward zones in deficit, linking them to zones in excess and not importing from any other zone.

3.1.2 Power Grid characterization

This section describes the characterization of the generated grids using architectural metrics. We are interested in the overall structure of the grid network, and ultimately, metrics that provide information about how the grid is structurally arranged as a whole. The metrics we feel are appropriate are *degree centralization*, *clustering*, *density*, and *modularity*. To measure these dimensions, we resort to graph theory, which has been extensively used (Hernández and Van Mieghem 2011, Martin-Hernandez 2013, Cetinay, Kuipers et al. 2016, Al-Shehri, Loskot et al. 2017). As a quick reminder, a graph is composed of node or vertex (the point at which pathways or links intersect) and links (pathways connecting nodes) (Costa, Rodrigues et al. 2007). In our case, a node is assimilated to a zone, while a link assimilates to a transmission line between zones.

Degree centralization measures how evenly distributed the grid is. It refers to the overall cohesion of the network, rather than to the relative prominence of individual zones (Analytic

Technologies 2000). A grid with high centralization would display, for instance, one zone trading power with many others, while one with low centralization would display power trading more evenly distributed across the network. The idea of centralization is that of the structural 'center' of the whole network, the zone or group of zones around which most of the power exchange is done.

Clustering is an architectural feature measured by the *clustering coefficient*, referring to how zones are connected and how much they are connected. This coefficient provides information regarding the degree to which zones in a grid network tend to cluster together; that is, a group of zones, which interact with each other more intensely and on a more regular basis than others, would be called a cluster. So in such a system, we would be interested in how many of one zone's power trading partners' zones trade between them. The more zones trading partners are interconnected, the more clustered the subset is said to be. This clustering within social networks is also called a clique; a clique is a group of people who interact with each other more regularly and intensely than others in the same setting.

Density measures how dense or sparse the network is; that is, the level of connectivity in the network. In a network, this metric looks at how connected nodes are, based on the total number of nodes. A dense network is a network in which each node is linked to almost all other nodes, while in a sparse network, the number of connected is low. A dense grid network would thus show power trading between almost all zones.

Modularity measures the ability of communities or modules to be formed in a network. High modularity in a network means that the nodes within a module have dense connections between them, but sparse connections between nodes in a different module. A grid network with high modularity would show higher trading between zones in a given cluster compared to trading between clusters in the network.

3.2 Development of Grid exploration tree

In this section, we describe the case study we intend to use. We also explain the generative mechanism we propose.

3.2.1 Case study description

For experiments, we develop a case study. This case study gives us the opportunity to focus on a specific situation, enabling us to shed more light to our research question. Using a case study, we have the opportunity to use real data and also apply our generative method to real world circumstances. The study is conducted on West African Power Pool (WAPP), which would constitute our grid.

This part of the world has a good Photovoltaic (PV) potential, but limited Concentrated Solar Power (CSP) potential, which is due to less direct irradiation and more important solar fluctuations (Hermann, Miketa et al. 2014). Regarding wind energy potential, western Africa offers 40 PWh (Hermann, Miketa et al. 2014). This region also generates its electricity from hydro, coal, gas, and oil, as well as biomass (WAPP 2011), which makes it a quite resourceful region. The countries mainly looked at in this study are ECOWAS (Economic Community of West African States), namely Burkina Faso, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo, and Benin. Each of the countries in this grid would be considered as a zone.

Those potentials are enormous for countries in this region, all of which have known some dramatic political and economic crisis. Yet, no considerable investment in energy infrastructure has been made (Vilar 2012). Access to energy is pretty limited there, with a power network still underdeveloped along with inadequate generation systems, leaving millions of people without electricity (Ouedraogo 2017). There is thus an urgent and critical need to improve electricity supply, distribution, and transmission in order to improve energy access for its increasing population and also offer avenues for economic growth (Legros, Havet et al. 2009).

Governments in this region have joined the global effort to increase the use of renewable energy, through different strategies to develop sustainable resource mix across countries and help these countries benefit from a better interconnection (WAPP 2011).

3.2.2 Generative Method Description

Grids are generated following a decision tree-like exploration (figure 4). The simulation is run over 20 years (2010-2030) with new grids generated every 4 years along the simulation. At the beginning of the simulation (year 2010), the initial grid is run. This grid represents the present state, with currently available generation fleet, transmission network, and present demand.

Once run, power deficits are assessed per zone or country, and the same action is implemented in all zones. For example, if we follow the option “build generation”, it is applied to all zones in deficit. Once all generation capacities are added in each corresponding zone, these zones altogether form a new grid. At the zonal level if, say, Ghana cannot cover its demand, a decision may be made to either build new plants with renewable resources – selection of the type of renewable is based on costs and availability – or build transmission lines coming from other countries to Ghana. In this case, not all countries are considered but only the ones that are not in deficit and not importing, as specified in section 3.1. By year 2014, deficits are again assessed. At that point, the two decisions are taken again, and so on, until year 2030. Figure 4 displays the tree-like exploration for grids generation. By year 2030, the grids generated are the results of transformations undergone in previous years throughout the length of the scenario. The total number of generated grids by year 2030 is 32. This corresponds to the number of data points to be used in our statistical analysis.

The scenario approach typically used in studies related to long-term planning in Africa (Bertheau, Oyewo, Cader, Breyer, & Blechinger, 2017; IRENA, 2013; Ouedraogo, 2017; Panos et al., 2016; Panos, Turton, Densing, & Volkart, 2015; Taliotis et al., 2014) presents different alternatives or scenarios. These scenarios help provide a picture of the eventual state of the grid in the future that would result from assumptions made. Here, the assumptions represent the changes, or predictions made about key factors related to energy planning, which capture uncertainty. Using this method, we are answering the question: "What happens if this or that factor change this way, or that way?" For instance, Panos et al. (2015) consider two scenarios, *Jazz*, with a focus on achieving economic growth through competitive and low-cost energy, and *Symphony*, with a focus on stronger policy regulations with priority given to sustainability and energy security. Both are run from year 2010 to 2050. These scenarios differ in the changes of key variables (GDP, per capita income, and CO2 price) over time, with Symphony assumed to present more significant changes.

Our method differs in two things: (1) changes in key variables are applied to the whole network for the whole scenario length, and (2) each of the alternatives are mutually exclusive throughout the scenario length. Unlike this scenario approach, our method enables different decision making or course of actions throughout the scenario. Different set of actions can be taken, following a trajectory conditioned by previous decisions and current knowledge. If a grid was generated in 2014 following addition of generation capacities, it may evolve to a different structure in 2018 by the addition of transmission lines. Our method assimilates to what Berkhout and Hertin, (2002) call *exploratory scenario*, in which "*the future is not only a continuation of past relationships and dynamics but can also be shaped by human choice and action,*" "*there is not one possible future only, uncertainty calls for a variety of futures mapping a possibility space,*" and "*the development of scenarios involves both rational analysis and subjective judgement.*" We feel it is a better representation of the impact of lock-ins and path dependency and a more accurate modeling abstraction of how grid system infrastructure come about and change over time.

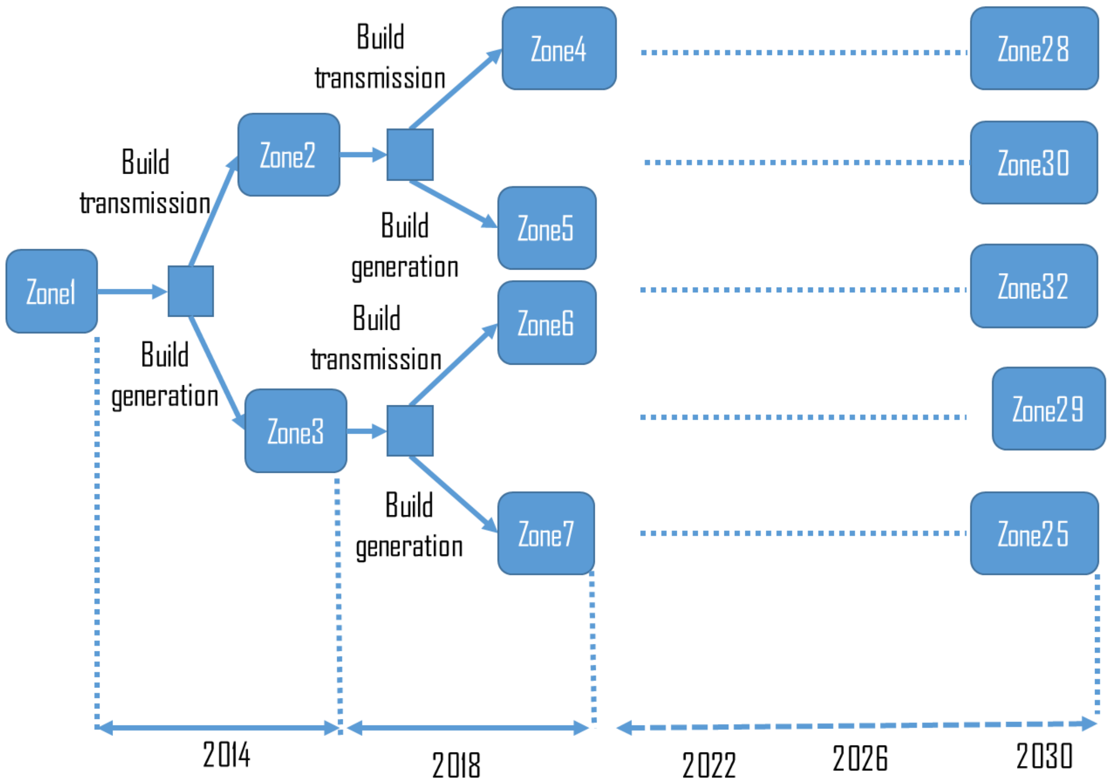


Figure 4: Power grid exploration tree

These grids are generated via a modeling framework. The model used capture key components of the power system, as well as relationships between them. To generate grids, the model needs to have certain requirements. As stated earlier, these requirements should be:

- *Technology explicit*: consider several power generation technologies (solar, wind, coal, geothermal, etc.) with all the corresponding operational constraints (minimum uptime, minimum downtime, ramp rate, etc.). This is important as it would provide a more accurate solution to unit commitment and dispatch problems. The penetration level of variable renewable electricity brings about a number of restrictions, more specifically, operational restrictions. By operational constraints, we mean factors constraining the operations of power system components. Among others, we have minimum power, minimum up and down times, planned/forced outage, etc. Modelling of the integration of variable renewable energy sources requires thus considering these details (Holttinen, Meibom et al. 2011). For example, efforts are made to develop more flexible generation units, with higher ramp rates and lower minimum generation levels, in order to compensate for potential slower response of certain conventional sources (Kannan and Turton 2013).

- *Data driven*: The model should be flexible, that is, present the opportunity to add or withdraw a generating or storage unit, a transmission line, a zone, etc., dependent on the collection and analysis of data. It allows the model to (1) account for every single component of the grid, which will enable more accurate financial and functional analysis of the system as a whole and (2) widen its applicability and make it adequate for a variety of studies. This requirement provides more flexibility to the model.

- *Spatially and temporally detailed*: The model should account for the system components on an individual basis, rather than through aggregation. It also should account for chronological variations in renewable source generation and in load. It is important, given the impact of the high variability caused by the share of renewable on backup power supply. For example, as the level of renewable penetration gets high, we need more flexible plants with higher ramp rates in order to minimize the possibility of unmet demand at a given time (Bhat, Begovic et al. 2014).

- *Equipped with stochastic algorithm*: The model should use stochastics methods in order to handle the variability or changes of renewable energy power generation. Decision-makers in the energy domain, have to deal with unexpected changes caused by demands and also renewable sources intermittence.

The full details of the development and features of the model are provided in the next chapter.

3.3 Correlation Analysis

Correlation testing is a method of statistical evaluation which helps show whether and how strongly two variables are related (Abbott 2010). This type of analysis is appropriate for our study as we are interested in establishing possible associations between various types of architectures and grid performance and determining the extent to which these variables vary together. For example, grids with the highest level of *clustering* are also the ones which display the most *reliability*. An appropriate conclusion to draw may be that the higher the *clustering* coefficient, the more reliable the grids tend to be. Going further, we also need to verify whether other factors affect reliability by studying the influence of not only *clustering* but also its interaction with *degree centralization* on the level of *reliability*.

We anticipate conducting this study in three steps: classify the data, perform correlation test, and perform multiple correlation analysis**.**

3.3.1 Classification of Data

In this phase, we look to specify what the dependent and independent variables are. In our case, the dependent variables are *reliability*, *sustainability,* and *affordability*. *Reliability* is measured by the ratio of the amount of demand met to the amount of total demands. *Sustainability* is measured by the amount of gas emission. *Affordability* is measured by all costs involved in the production, transmission, and distribution of electricity in the grid. These variables represent the grid performance. The independent variables are the grid metrics mentioned above in section 3.1.2., namely *clustering*, *degree centralization, modularity* and *density*. They represent the metrics used to characterize the different types of architectures of the power grid.

3.3.2 Correlation Test

In this phase, we look to find out whether a relationship exists between two variables, one dependent and one independent variable. This is done by conducting a statistical correlation test (Farrar and Glauber 1967). Each one of the independent variable is tested against each one of the dependent variable or hypothesis variable (1 on 1 correlation analysis). We can phrase the hypothesis in the form of questions:

Is *density* related to affordability? Or is *modularity* related to affordability?

The relationship sought here is captured by a numerical value, which indicates the extent to which the two variables vary together. This numerical value is called the *Pearson correlation coefficient*, or *r*, which ranges from -1 to +1. The closer the value of *r* get to either +1 or -1, the stronger the relation between the two variables. If the value of *r* is close to 0, it means that there is no relationship between the variables (Geher and Hall 2014). If *r* is positive or negative, it indicates that the increase in the independent variable causes the dependent variable to increase or decrease, respectively. Eq1 below present the formula of *r*.

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{s_x}\right)\left(\frac{y_i - \bar{y}}{s_y}\right) \text{(Eq1)}$$

With s_x, s_y, *xbar*, *ybar* and *n* being the standard deviation of variable *x*, standard deviation of variable *y,* mean of all values of variable *x*, mean of all values of variable *y*, and the total number of values (sample size), respectively.

While *r* provides valuable information about association between two variables, r^2 can help further our understanding. The value r^2*,* called *coefficient of determination,* represents the amount of variation in one variable that is associated to the variation in the other (Beaumont 2012). This is the measure of the proportion of explained variation compared to the total variation (Beaumont 2012).

To perform this test, some assumptions need to be made regarding the data, including level of measurement, absence of outliers, normality, and homoscedasticity (Tabachnick and Fidell 2006).

The level of measurement refers to the type of each variable. For this test, each variable should be continuous rather than categorical. Continuous variables are quantitative variables. In our case, all of our variables are numerical as they represent the values of our architecture metrics and the output of our model. Absence of outliers refers to not having outliers in either type of variable. The reason for this is that having an outlier may cause skewness in the results. An outlier is an observation in a data set which appears to be at odd with the remainder of that set of data (Johnson and Wichern 2014). To determine the presence of outliers, we intend to draw a boxplot, which is a good tool for visualizing variation information in the data, describing the distribution of the data, and identifying potential outliers (Chambers, Cleveland et al. 1983). It is our belief that we will not have many outliers, if any, since our generation mechanism is consistent in terms or rules and conditions (see Section 3.2). We plan to remove the eventual outliers. Homoscedasticity refers to the case in which the error term or residual, remains almost the same across all values of the independent variables (NIST/SEMATECH 2003). To test to see whether the data is homoscedastic, we plot them on a scatterplot and visually inspect the graph's shape. The points on the scatterplot should cluster along a straight line, in such a way the distance between the points and the line is about the same (Mertler and Vannatta 2010). Normality can be verified by normal probability plot (Ghasemi and Zahediasl 2012), which is a graphical technique helping to assess whether or not the data are normally distributed. Data should be plotted against a theoretical normal distribution in such a way that values ought to draw an approximate straight line (NIST/SEMATECH 2003). Values away from this straight line would indicate shift from normality.

The sample size n is also subject to constraints, as an inappropriate size would undermine the results of the test (Bonett and Wright 2000). Numbers vary, though David (1938) suggest a minimum of n = 25, for conducting a Pearson correlation test. To obtain a 100 (1 – α) % confidence interval with a desired width w (Upper Limit minus Lower Limit), the required size can be found by solving the following equation:

$$n = \left(\frac{z_{\alpha/2}\sigma}{ME} \right) \text{ (Eq2)}$$

With α, $z_{\alpha/2}$, σ, ME being the degree confidence, the critical value in the z-table (Wu, Hayes et al. 2001), the standard deviation and the margin of error (which is referred as half the width of the confidence interval (Salkind 2010)), respectively.

3.3.3 Multiple Correlation Analysis

In this phase, we look to find out whether and how strongly many independent variables have an effect on each of the dependent variable. For this purpose, we use multiple correlation testing to measure for example, the relative influence of *density,* and *degree centralization* on reliability. This step would also help determine which combination of independent variables performs the best out of all of the possible combinations in terms of association with the hypothesis variable.

In addition to the assumptions made in Section 3.4.2., this test also requires the data not to show multicollinearity (Yoo, Mayberry et al. 2014). Multicollinearity occurs when two or more independent variables are highly correlated with each other (Paul 2006). The existence of a significant relationship between these variables makes it difficult to understand which independent variable contributes to the variance in the dependent variable. The assumption of lack of multicollinearity would be evaluated by examination of Correlation Matrix, which is a symmetric array of correlation coefficient *r* between all independent variables (Joshi 2012). Remedial measures to multicollinearity, according to Joshi (2012), would include either to dropping one or several independent variables if possible, or performing the technique of Principal Component Regression if not. This method, which is a regression analysis technique that is based on principal component analysis, helps eliminate some of the principal components with very low variance, in the regression step (Dodge 2003).

One way to accurately assess the influence on the dependent variable is to break all of the correlations down, computing the value of the multiple correlation coefficient, *R* (Abdi 2007). *R* indicates how much of the change in the dependent variable is related to all of the independent variables, or as Abdi (2007) puts it, "*…can also be interpreted as the proportion of the variance of the dependent variable explained by the independent variables…*"

For example, a value of $R = 0.9$ between *density*, *modularity,* and *reliability* suggest that the combined correlation between those two variables (*density*, *modularity*) with *reliability* is 0.9. In other words, we could, with little uncertainty, estimate how reliable a grid would be, if we know nothing more about the grid than its level of density, and degree centrality. The formula or *R* is computed as follow:

$$R = \sqrt{\frac{1}{1-\left(r_{x1,x2}\right)^2}\left(\left[\left(r_{y,x2}\right)^2 + \left(r_{y,x1}\right)^2\right] - (2r_{y,x1}r_{y,x2}r_{x1,x2}\right)} \text{ (Eq3)}$$

With $r_{x1,\,x2}$, $r_{y,\,x2}$, $r_{y,\,x1}$ being the correlation coefficient between variable x_1 *and* x_2 (independent variables), correlation coefficient between variable *y and* x_2 (y being the dependent variables), and correlation coefficient between variable x_1 *and y,* respectively.

Similarly to *r*, *R* is comprised of values between -1 and +1, with stronger correlation as values approach these extremes, and weaker ones as values approach 0. Another similarity is the value of R^2, which can be interpreted as the proportion of variance of the dependent variable explained by the independent variables (Abdi 2007). R^2 indicates how much variation in the dependent variable is due to the combination of independent variables.

We believe these tests would allow us to assess relationships between the grids architectural metrics and the grids performance. By performing the correlation test, we look to find the existence and strength of association between each architectural metric and each outcome metric. In doing so, we can already identify strong or not so strong associations. However, this may not be sufficient to draw definitive conclusion, given the complexity of the system and the variety of factors it is subjected to. Rarely, if ever, are changes of a single factor solely responsible for changes in another factor. The multiple correlation test is helping to estimate the association of a combination of architectural metrics with the outcome metrics. In doing so, we can, more accurately, explain changes in the outcome variables and ultimately draw appropriate conclusions.

CHAPTER 4

MODEL DEVELOPMENT

In this chapter, we present the steps undertaken in building the model. Using this model, we can start to explore the ways to answer our research questions. In the 1st section, we present the model conceptually, presenting its mechanism and defining key components considered. In the 2nd section, we present the model specification, that is, how systems mechanisms and components are represented in the modeling formalism. The last section describes the implementation.

4.1 Model Conceptualization

Spark! is a bottom-up discrete-event system model that simulates the time dependent behavior of large-scale power systems, taking into account the combined effects of the intermittence and stochastic nature of renewable energy resources and their forecast ability, the operational constraints of conventional sources, geographical information, transmission network, and a flexible time resolution. As an hourly chronological model with discretized components and a zonal structure, *Spark*! captures costs of operating generators, reliability and emission at various locations in the network and runs security constrained unit commitment and economic dispatch activities. The model performs energy planning, by analyzing expansion plans for electricity generating, transmission, and electrical storage technologies in the long term while ensuring reliability of the system in the short term. It captures all components composing the power system, and represents them as individual and autonomous models, that interact between them. In being autonomous, they decide for themselves what to do, when to do it, and how it is to be done. Each of them is embodied with the ability to communicate, respond to, and send messages one another.

4.1.1 Conceptual Modeling

This model is described as generally informal and typically graphic depictions of the real systems, containing information related to the overall functionality of that system (McKenzie 2010). The model should capture all aspects mentioned in Table 3.

We use a Unified Modeling Language (UML) class diagram. A class diagram consists in defining the system's classes, their characteristics or attributes, and their actions, which we assimilate here to links or relationships between objects. Objects are instances of classes, identifiable within the limits and scope of the system considered (Van Dam, Nikolic et al. 2012). A class is composed of objects sharing the same attributes and prerogatives. An object can be any person or thing applicable and relevant to our system. For example, although several power plants exist in Ghana, we would only model one class, called Generators, which would represent the ensemble of all power plants (which are the objects here). The same logic is applied to all other classes. Classes have a name (upper section), some attributes (middle section), and actions or operations (lower section) assigned to them. Name is self-explanatory. Attribute indicates the characteristics inherent to the class; it highlights the criteria over which the class is identified and implies a set of features ascribed to it. Actions refers to all possible prerogatives of the objects constituting the class.

Figure 5 shows a simplified UML class diagram conceptual model of a power system. The power grid (inter-zone) is decomposed into geographic zones, which are connected via transmission lines. Each zone has loads, generators, and storage units. Transmission lines enable the transmission of power between zones. Each zone has a dispatcher which manages the supply of power from the generators to the loads. The dispatcher also manages the exchange of power and information between zones, to meet all demands and to determine market-clearing prices, while considering all constraints. Generators are committed daily or weekly by a unit commitment component, which schedules them when available, technically feasible, and cost effective, to supply power to the loads. Dispatchers manage the local power distribution using hourly information of load demand and dispatch-able generation capacity and cost. Transmission lines and unit commitment are not assigned zones. Storage and generating units can be of different technologies.

Table 3: Power system components

Agent: Load Model Attributes: • Type of demand: Residential, Commercial, Industrial • Zone: Name of the zone it belongs to Objectives: Request power Behaviors: • Create aggregate load from customer demand • Compute the amount of demand met
Agent: Generator Model Attributes: • Name • Technology: committable, not committable • Zone: Name of the zone it belongs to • Operational constraints: ramp rate, minimum uptime and downtime, planned and forced outage, minimum operating capacity • Fuel type: oil, gas, geothermal, nuclear, biomass, biogas (No fuel when technology is not committable) Objectives: Supply power Behaviors: • Create supply quantity from power plants demand and specify on what prices to charge the capacity to submit • Update the capacity after hourly use • Compute hourly operating costs and total usage costs • Store unused power quantity
Agent: Dispatcher Model Attributes: • Name Objectives: Perform economic dispatch. Balance power supply and demand Behaviors: • Dispatch generators hourly, based on availability • Engage in electricity market trading through bids to buy or offers to sell electricity • Accept or reject bids based on economic gain.
Agent: Transmission lines Model Attributes: • Origin • Destination • Capacity • Loss coefficient: Loss during transmission Objectives: Supply power over transmission grid to meet dispatchers' requests. Behaviors: Transmit electric power from zones to zones
Agent: Storage Model Attributes: • Name • Technology: Type of storage • Zone: Name of the zone it belongs to • Operational constraints: Planned and forced outage, maximum capacity Objectives: Supply power Behaviors: • Create supply quantity from storage units and specify on what prices to charge the capacity to submit • Update the capacity after hourly use • Compute hourly operating costs and total usage costs
Agent: Unit commitment Model Attributes: • Name Objectives: Commit power generators Behaviors: • Estimate net load based on variable generation availability • Schedule generating units ahead, by deciding when to turn them on/off • Decide how much power to commit per generator, based on costs, transmission lines and generators constraints

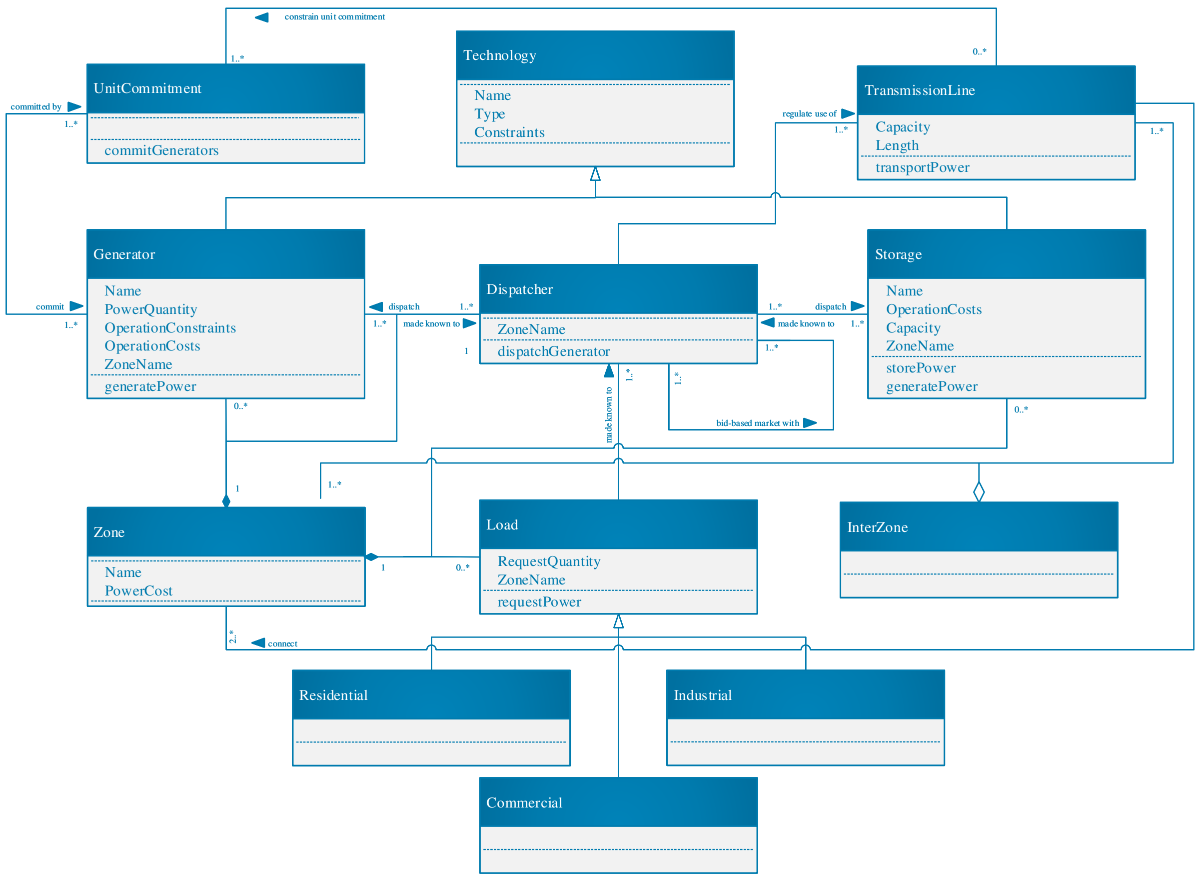


Figure 5: Conceptual model of a power system

4.1.2 Model Formalism

This model is the implementation or execution of the conceptual model. In our case, we elect to use a formalism, as it allows the description of the system in a formal, mathematically grounded way. That way, we build the model in a structured manner, following clear guidelines to specify the behavior of each component of the system.

Simulation Model Formalism

According to Zeigler, Praehofer et al. (2000), a formalism has sound mathematical foundation and rigorous semantics. Zeigler (1976) formally defines a system as a $S = (T, X, Y, Q, q_0, \delta, \lambda)$, where T is the time base, X is the set of input, Y is the set of output, Q is the set of states, q_0 is the initial state, δ: $Q \times X \rightarrow Q$ is the transition function, and λ: $Q \rightarrow Y$ is the output function. In the next sections, we briefly define the main formalisms and give the rationale for our formalism choice.

Types of Formalism

Zeigler, Praehofer et al. (2000) present three basic modeling formalisms, namely Discrete Time System Specification (DTSS), Differential Equation System Specification (DESS), and Discrete Event System Specification (DEVS).

DTSS represents systems over a discrete time base. This formalism is appropriate for systems that change their states at regular intervals, and input and output are only computed at the end of these intervals (Barros 1997). It therefore assumes a stepwise execution. In this case, the time base T is a set of integers, $T = \{t_1, t_2, \ldots t_n\}$, with $t_1, t_2, ..t_n \in N$, and δ: $Q \times X \rightarrow Q$ is the single step transition function. At each time unit, the system checks its inputs and its current state, produces an output, and then changes its internal state using δ (Barros 1997).

DESS formalism represents systems over a continuous time base. This formalism does not specify a next state directly through a state transition function but rather specifies the rate at which state variables change, via differential equations (Cellier 1991). In this case, the time base T is a set of real numbers, $T = \{t_1, t_2, \ldots t_n\}$, with $t_1, t_2,..t_n \in R^+$ (positive numbers since time is always positive), and δ: $Q \times X \rightarrow Q$ is the rate of change function. At any time, the system checks its state and its input value, produces an output and computes its next state at any time in the future, via integration method function.

DEVS formalism represents systems over a continuous time base. This formalism is appropriate for event-driven models; that is, systems whose states change anytime an event takes place. The state trajectories or changes are produced by state transition functions δ_{ext} and δ_{int} that are activated by external or internal events, respectively (Zeigler 1976). In this case, the function

δ is represented by both δ_{ext}: $Q \times X \rightarrow Q$ and δ_{int}: $Q \rightarrow Q$, and the system described as a tuple S = ($T, X, Y, Q, q_0, \delta_{ext}, \delta_{int}, \lambda$). δ_{int} (s) = s' means that δ_{int} enables the transition from state *s* to *s'*, triggered by internal mechanism, and δ_{ext} ((s, *e*), x) = s' enables the transition from state *s* to *s'* triggered by external input *x* with *e* being the elapsed time before the state transition.

Our choice of Modeling Formalisms

For the purpose of our research, we find DEVS the most adequate. Our choice is mainly based on two criteria: modularity and hierarchy (Zeigler 1976, Xia, Xu et al. 2016). Modularity is the ability for a system to be broken down into modules, not only able to effectively communicate together via information exchange to reach a general common objective, but also able to meaningfully assemble and collaborate for a specific purpose (Tolk 2010). Hierarchy suggests a multi-layer structure of the system. The support of this formalism for modular and hierarchical component-based modeling can be shown by the formalism itself (Wainer 2009).

DEVS formalism enables the description of the inputs, outputs and states of a model, as well as the relationships among them. Models expressed in this way are called *atomic*. Modularity is enforced as these models' interactions with their environment take place only via its input and output ports (Solcány 2008). In that sense, no direct access by any other external components or models to internal state is possible. An *atomic* model has a number of input ports, with each of them having a defined set of possible values that can appear in those ports. The same principle is applied to the outputs. The model states transition from one to another using the functions δ_{ext} and δ_{int}. The function δ_{ext} computes the new state of the model in the case of external events, which are triggered by external inputs to the ports. The function δ_{int} computes the new state when no external event occurs but rather when internal events do. These events depend on the time since the last state transition. Each atomic model has its functions specified in its own way, according to its role in the system, as a whole.

The *atomic* models can be used as building elements, which are part of a larger model called the *coupled* model (Solcány 2008). Such model describes its components (either atomic models or other coupled models) and specifies their interconnections. The property *closure under coupling* ensures that both atomic and coupled models use the same interface protocol (Zeigler 1984). That way, the atomic or coupled model can be used as a component in another larger model, enabling hierarchy in the overall model design. Each *coupled* model has thus identical inputs and outputs as the *atomic* model, which makes possible for the *coupled* model to be treated as *atomic* and coupled in a higher hierarchy of models (Moon 2014). Unlike *atomic* models which require functions to specify their behavior, *coupled* models don't. Rather, they specify couplings between their components. There exist three types of coupling: External Input Coupling (set of links connecting input ports to components input), External Output Coupling (set of links connecting components output to output ports) and Internal Coupling (set of links connecting components output to components input) (Goldstein, Breslav et al. 2013). These connections all follow the same protocol; that is, before sending a message to the target component, the output specification of the source is mapped to the input specification of the target, protecting the integrity of the message throughout the hierarchical structure.

4.1.3 Model level of abstraction

Similarly to single-node models (Tande, Korpås, Warland, Uhlen, & Van Hulle, 2008) and transshipment models (Nygard et al. 2011), *Spark*! represents the grid system at the activity level, capturing tactical decision making to enforce system balance. The focus is on the power plants, demand types and quantity, transmission and distribution systems and storage units, how they function individually and collectively, and how their functioning contributes to fulfilling the goal of the power system. *Spark*! models the grid as a network of balancing areas and authorities. Nodes in *Spark*! represent balancing areas or zones (both terms will be used interchangeably until the end of this document), connected via transmission lines (Figure 6). A balancing area (BA) is a geographical location with specified generation fleets, load profiles, and a balancing authority. A balancing authority is the entity responsible for integrating resource plans ahead of time and maintaining load-generation balance within a balancing authority area at all times.

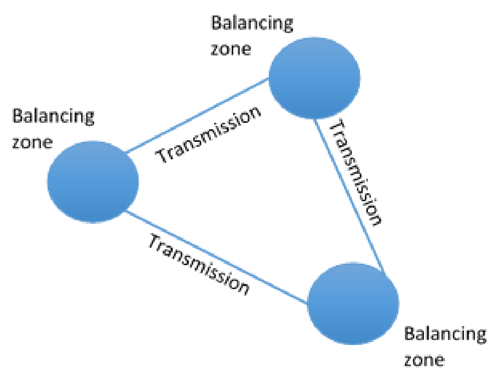


Figure 6: *Spark!* power grid system abstraction.

Balancing area operations are conducted in a coordinated manner in order to promote cost savings, more efficient resource usage, and integration of renewable energy (Katz, Denholm, & Cochran 2015). This coordination takes place within the boundaries of balancing areas through coordinated dispatch, addressing the economic dispatch (ED) problem and also beyond the boundaries of balancing areas through coordinated scheduling, addressing the unit commitment (UC) problem.

The UC problem deals with determining the optimum amount of time during which a generating unit should be scheduled (Saravanan, Das, Sikri, & Kothari 2013). The UC is a schedule, consisting in committing generators ahead of time to meet the expected demand over that very time period. It determines which of the generators can be operated, considering economic, regulatory, and technical constraints (Harris 2011). Economic constraints suggest that the scheduling is the least expensive based on generators operating costs and transmission costs. Regulatory constraints refer to set regulations; for example, reserve margin requirement (PJM 2016). Technical constraints concern generators and transmission line capacity, generators minimum uptime, downtime and planned outage. The ED problem deals with identifying the optimal use of generating units in the least costly and environmentally damaging manner. ED mainly brings units on line, based on operating costs and the availability of renewable energy resources. The generating units in question here are the ones previously committed during the UC phase. The objective is to balance the system and dispatch necessary units in real time, as opposed to UC which is carried out ahead of time.

The coordinated scheduling is carried out by a balancing network authority (BNA), which, like a vertically integrated entity, has direct control and access to all generating units in all balancing areas. This entity does not belong to any balancing area and looks to schedule all units in the grid network based on weather data information and load forecast. This consolidation co-optimizes the generation fleet for maximum economic benefit and least-cost renewable integration and also provides the benefits of reserve sharing. The coordinated dispatch is carried out by a balancing area authority (BAA), which is specific to each balancing area. This balancing ensures, based on generation/consumption exchange information, that demand and supply are matched at all times. If not, the balancing authority takes appropriate actions, including managing trading of electricity with other balancing authorities. This trading is a bid-based bilateral exchange market (Dempsey 2011), where bids to buy and/or offers to sell electricity are shared between areas in a horizontally integrated structure. Depending on their needs, buyers and sellers of electricity agree to a transaction, and financial transactions are handled bilaterally. Once agreements are met, power is physically exchanged between balancing areas.

4.1.4 Model spatial and Temporal Framework

The model presents a high spatial and temporal resolution. The level of temporal details enables the model to account for the dramatic change in the patterns of power system behavior due to the randomness introduced by solar or wind sources (Makarov, Diao et al. 2015). The level of geographic detail enables the model to account for each single generating and storage unit in each zone. *Spark!* is an hourly chronological model. This resolution allows the model to capture plant cycling limits and costs and minimum on and off periods (Mai, Drury et al. 2013). *Spark!* considers the seasonal and diurnal variations in demand and resource profiles. The number and length of time slices are defined by the user using three levels (seasonally/monthly, daily, and hourly). Moreover, the model accounts for transmission lines linking different zones or areas. Modeling the transmission system allows to better identify locations with accessible high-quality renewable resources, power deficit, or any other phenomenon that might require actions. The model does not aggregate regions, technologies, or any other components, enabling study at the individual level. The spatial distribution is thus a function of the input data rather than the user assumptions or abstractions. This spatial resolution allows us to more accurately represent the locational differences in renewable resource quality, load pattern, and generating and storage technology.

4.1.5 Model Constraints

Major constraints in *Spark!* include load balance, reserve requirements, renewable resource limits, thermal power plant constraints, economic and transmission constraints.

4.1.5.1 Load Balance Constraints

The load balance constraint requires that for each time unit, and everywhere in the network, supply match demands. It means that generation within a given location and power imports into this location has to equal the sum of the local demand and any exports out of that location.

4.1.5.2 Reserve Requirements Constraints

We consider two types of reserves: operating and planning. Planning reserve requirements ensure that generation can cover peak demand by a reserve margin. In the model we propose, this margin is set to 15% (EPIS 2016). Operating reserve requirements ensure that the planning of generators' schedules can withstand the uncertainty due to unforeseen generators or transmission lines breakdown.

4.1.5.3 Renewable Resource Profiles

Based on the input database, the model computes the limits of deployment and output characteristics of wind, solar, and hydropower technologies. *Spark!* relies on mathematical models used in other peer reviewed studies to estimate the generation quantity. For PV technology, for example, the output would depend on the area considered and the irradiance at a given location.

4.1.5.4 Thermal Power Plants Constraints

Unlike renewables, thermal, or conventional power plants are subject to unit commitment. In other words, these technologies can be scheduled ahead of time. However, modeling these types of plants requires taking into consideration operating constraints. These include minimum generation, ramp rates, start-up and shutdown issues, minimum on and off times, and outage rates. These details are critical as they help perform an accurate generators schedule. For example, start-up and shutdown events, as well as minimum on and off period constraints, determine which plant(s) should be generating or idle.

4.1.5.5 Economic Constraints

Beyond helping to achieve an optimal generators schedule, the unit commitment problem highlights the importance of operating costs (Tahanan, van Ackooij et al. 2015), both at the generator level and the transmission line level. This schedule is made, ensuring that the least expensive option is selected. Also, the power dispatch (PD) problem presents economic constraints, as it requires identifying the optimal use of electricity generators, in the least costly and environmentally damaging manner. The dispatch has to be done, considering costs to generate power.

4.1.5.6 Transmission Constraints

The transmission system in *Spark!* is modeled as a simple transportation model. Power shared between areas or zones in the network via transmission lines is only constrained by the capacity of those lines.

4.1.6 Model Run Mechanism

The default simulation time increment is one hour. This time unit captures the hourly fluctuations in daily electricity demand as well as weather changes. *Spark!* runs in two modes, *forecast* and *actual*. In *forecast* mode, Spark-UC (model component tackling the UC problem), based on forecasted meteorological (wind, water, solar) and load data, generating technology characteristics data and transmission lines characteristics data, computes the *net load* and schedules the generating units needed to meet the remaining expected demand. The *net load* represents the system load not covered by renewables, but rather by conventional sources. In mode *actual,* Spark-ED (model component tackling the ED problem) proceeds to dispatch power generators in real time, based on operating costs and the availability of renewable energy resources, to meet current load. It dispatches generators with the lowest operating costs first and the ones with the highest costs last if needed. Supply and demand quantities are compared in order to assess an eventual need for power and engage in power trading if needed. This trading is carried out through bids to buy and/or offers to sell electricity if imports prove cheaper than use of local generators and storage units. Spark-ED executes multiple trading rounds until all offers are settled and no further trade is made. The system has reached equilibrium. Figure 7 shows the conceptualization of these mechanisms. Algorithms used in Spark-ED and Spark-UC are explained in more details in Section 4.1.6.

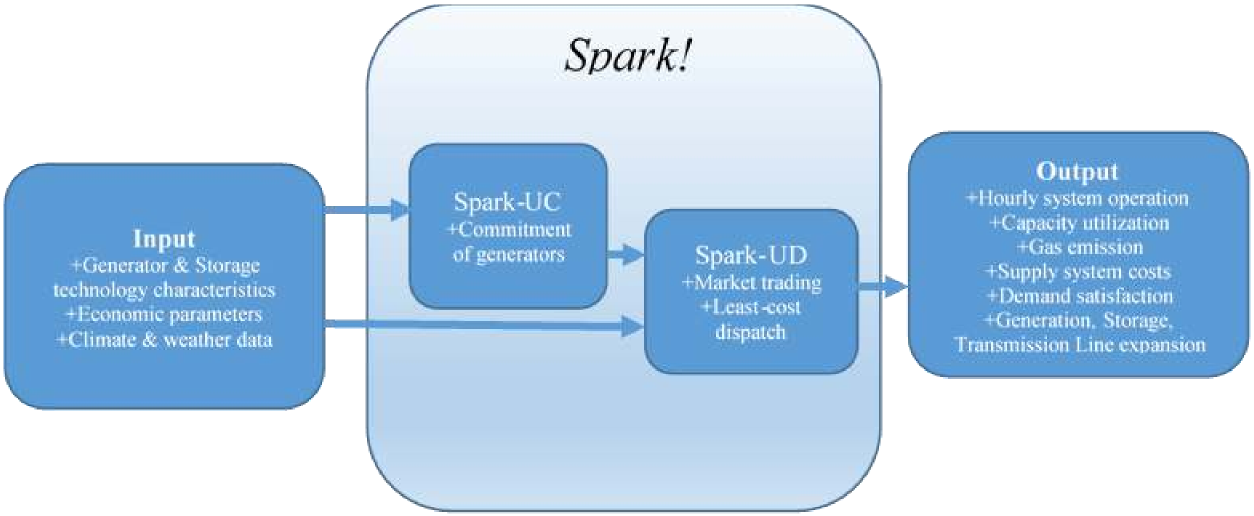


Figure 7: Schematic of model mechanism.

4.1.6.1. Unit Commitment

The Unit Commitment (UC) problem, also referred to as cost-based unit commitment problem, consists in scheduling the ON/OFF times of plants ahead of time in such a way to minimize the costs associated with hourly generation (Jabr 2013). The BNA is responsible for this scheduling, ensuring that expected demands are matched.

4.1.6.1.1 UC problem formulation

This section provides details regarding the notations used throughout the paper. We also formulate the problem and present the equations and algorithm used to address the UC problem. Table 4 displays all the parameters used in our method. Table 5 displays all the lists, which are the sequence of units or power plants ordered based on their utility. Table 6 displays all the sets used in our method, which correspond to the indices used in variables and equations.

Table 4: List of variables in UC problem

Name	*Description*
comOutput	Output generated by power plants committed
downTime	Number of hours down, or OFF
fixCost	Fixed costs
fuelCost	Fuel costs
Load	System total load
maxPower	Maximum power output that can be generated
minDownTime	Minimum number of hours units need to be down
minPower	Minimum power output needed for a unit to be committed
minUpTime	Minimum number of hours units need to be up
netLoad	System load, served only by conventional sources
nomCapacity	Nominal unit capacity
opReserve	Operating reserve
powerStored	Power output stored
prvComCapacity	Output generated by unit at previous hour
renOutput	Power output generated by renewable sources
shutDownCost	Shut-down costs
startUpCost	Start-up costs
storageCapacity	Maximum power output that can be stored
storageEfficiency	Storage efficiency
storageLevel	Quantity of power output in storage at each hour
totGenCost	Total generating costs
transCost	Transmission costs
transCapacity	Transmission lines capacity
transFlow	Flow of power transmitted through lines
unitOutput	Output generated by power plants turned ON, committed or not
unitUtility	Utility of each unit
ups	Total number of consecutive hours during which units are up
upTime	Number of hours up, or ON
varCost	Variable costs
vLoad	System load served only by renewable sources

Table 5: List of all lists in UC problem

Name	*Description*
commitList	List of conventional units committed during the current commitment period
renUnitList	List of renewable source units available in the power network
prevHG	List of units committed during the previous hour during the current commitment period
prvCommitment	List of units committed during the previous commitment period

Table 6: List of set in UC problem

Name	*Description*
u	Power plants or unit index
h	Time periods (hour in our case)
l	Transmission lines between zones
i	Time step in the solving loop
s	Storage unit index
t	Total time steps in the solving loop

4.1.6.1.1.1 Objective function

The UC problem can be formulated as an optimization problem. The objective is to minimize the total generation cost, which is defined as the sum of different cost items, namely: start-up and shutdown, fixed, variable, fuel, and transmission-related costs (Eq4).

$$\mathit{Min}\ \text{totGenCost}$$

$$\text{totGenCost} = \sum_{u,i} \text{fixCost}_{u,h} + \sum_{u,i} \text{varCost}_{u,i} + \text{unitOutput}_{u,i} \times \text{fuelCost}_{u} + \text{sCost}_{u,i} + \text{transCost}_{i,l} \times \text{transFlow}_{i,l} \quad (4)$$

$$\text{sCost}_{u,i} = \begin{cases} \text{shutDownCost}_{u,i} \\ \text{startUpCost}_{u,i} \\ 0 \end{cases} \quad (5)$$

The term *sCost* (in Eq5) is equal to either the start-up cost, shutdown costs or 0, depending on whether or not a unit is turned ON. If a unit is ON at time *i* and not at time *i-1*, the term *sCost* is equal to shut-down costs. It is equal to start-up costs in the opposite case. If a unit is ON at time *i-1* and also at time *i,* or OFF at time *i-1* and also at time *i,* the term *sCost* equals 0.

4.1.6.1.1.2 Constraints related to the demand

The main constraint here is to meet the demand at all times during the commitment period in all zones throughout the network. The total power produced by all the generating units committed present in the whole network should be equal to the total load in the whole network.

$$\sum_{u,h} \text{comOutput}_{u,h} = \sum_{h} \text{netLoad}_{u,h} + \text{opReserve}_{h} \ (6)$$

$$\text{opReserve}_{h} = k \times \sum_{u} \text{netLoad}_{u} \ (7)$$

$$\sum_{h} \text{netLoad}_{h} = \sum_{h} \text{Load}_{h} - \sum_{h} \text{vLoad}_{h} \ (8)$$

The term *opReserve* (Eq6) designates operating reserve. This is a key concept to ensure the balance supply-demand. The reserve serves as a cushion to guarantee that planning of generators' schedules can withstand uncertainties caused by changes in load profile or generator breakdown (EPIS 2016). The term k in (Eq7) indicates the percentage of load quantity that should be considered for reserve purposes. For example, the NERC (North American Reliability Corporation) sets the reference margin to 15% for thermal-dominated systems (EPIS, 2016), that is, k = 15% of *netLoad* must be covered, on top of the value of *netLoad* itself. In this research, we assume that the reserve requirements considered are an aggregation of all types of reserves, namely spinning, non-spinning, frequency-response, and replacement reserves. The term *netLoad* (Eq8) designates the load to be met by conventional sources. This quantity is obtained by subtracting the quantity *vLoad* from the system total load. Once computed, we can then know the quantity of power required, and commit the necessary plants.

4.1.6.1.1.3 Constraints related to generators' power output

The minimum power output is determined by the must-run generation level of the unit if it is committed. If a unit is committed, its output must be greater than or equal to its minimum generation capacity but less than or equal to its full nameplate capacity.

$$\text{minPower}_{u} \le \text{comOutput}_{u,h} \ (9)$$

$$\mathrm{maxPower}_{u} \geq \mathrm{comOutput}_{u,h} \quad (10)$$

4.1.6.1.1.4 Minimum up and down times

The power output in a given period depends on the output levels in the previous periods. Conditions in Eq11 and Eq12 have to be met before a unit can be uncommitted and committed, respectively. If a unit is OFF or ON, it must remain OFF or ON for at least *minDownTime* or *minUpTime* hours, respectively (Anders, 2005).

$$\mathrm{upTime}_{u,h} \geq \mathrm{minUpTime}_{u,h} \, (11)$$

$$\mathrm{downTime}_{u,h} \geq \mathrm{minDownTime}_{u,h} \, (12)$$

4.1.6.1.1.5 Storage-related constraints

Storage units are subject to the same constraints as generating units or power plants. In addition, there are constraints which are specific to storage. These constraints include the storage capacity and charge/discharge efficiency. The first constraint imposes that the power stored is limited by the storage capacity.

$$\mathrm{powerStored}_{s,h} \leq \mathrm{storageCapacity}_{s,h} \, (13)$$

The energy stored at a given time depends on the quantity stored in the previous period and the charge/discharge efficiency. This efficiency parameter captures the losses between energy stored and retrieved. This is the ratio of energy retrieved to energy stored. The term *storageLevel* constitutes the amount of power available for usage.

$$\mathrm{storageLevel}_{s,h} = \mathrm{storageCapacity}_{s,h} - \mathrm{powerStored}_{s,h} \times \mathrm{storageEfficeincy}_{s} \, (14)$$

4.1.6.1.1.6 Network-related constraints

The flow of power between zones is limited by the capacities of the transmission lines.

$$\mathrm{transFlow}_{h,l} \leq \mathrm{transCap}_{h,l} \quad (15)$$

4.1.6.1.2 UC modeling

In addition to the equations presented in the previous section, we propose a new algorithm based on priority list using a utility function, which sets up the order of commitment. The algorithm is composed of different steps, which are sequentially passed through. Figure 8 displays those steps, which are discussed below.

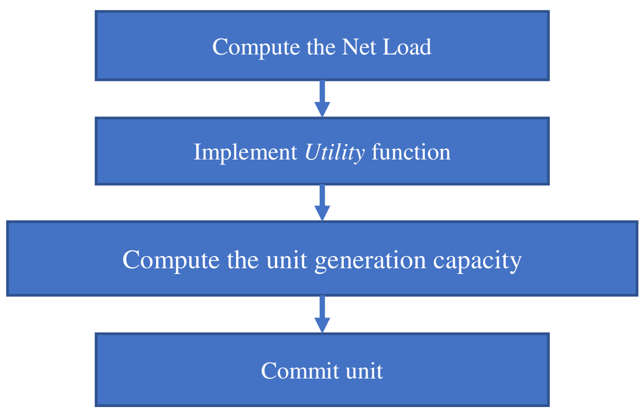


Figure 8: Flow chart of our developed algorithm

4.1.6.1.2.1 Compute the net load

As mentioned earlier, even though renewable source units are not committable, it is important to account for the net load and how this value is computed. In this step, the objective is to find out how much demand would be met based on the expected power output from renewable, zone (geographical location with specific supply fleet and load profile) by zone. All renewable energy source units are placed into a list *renUnitList* and sorted by output. The plants of smaller output are put ahead of the plants of larger output. The output represents the forecasted values of generation quantity from renewable sources.

$$\textit{if}\ \text{Load}_{z,i} > 0 \text{ and } \text{Load}_{z,i} >= \text{renOutput}_{u,i} \text{ and } \text{renOutput}_{u,i} > 0 :$$
$$\textit{then}\begin{cases} \text{Load}_{z,i} = \max\,(0, \text{Load}_{z,i} - \text{renOutput}_{u,i}) \\ \text{renOutput}_{u,i} = 0 \end{cases} \qquad \text{(Eq16)}$$

Eq16 checks three conditions for each zone considered: (1) there is demand in a given zone, (2) this demand is greater than the overall output generation expected from renewable sources, and (3) there is output generation from renewable sources. Going through the *renUnitList* list, the zone demand is reduced by the amount of power expected to be produced by each element of that list. The zone demand to be matched by renewables is determined that way. At the same time, the zone demand to be matched by conventional sources is also deduced. This is what is called the net load. In Eq16, we consider the case where renewable generations are not enough to meet the demands in a zone.

$$\textit{if}\ \text{Load}_{z,i} > 0 \text{ and } \text{Load}_{z,i} < \text{renOutput}_{u,i} \text{ and } \text{renOutput}_{u,i} > 0 :$$
$$\textit{then}\begin{cases} \text{Load}_{z,i} = 0 \\ \text{renOutput}_{u,i} = \text{renOutput}_{u,i} - \text{Load}_{z,i} \end{cases} \qquad \text{(Eq17)}$$

Eq17 checks three conditions as well, for each zone considered: (1) there is demand in a given zone, (2) this demand is lesser than the overall output generation expected from renewable sources, and (3) there is output generation from renewable sources. Like the previous case, going through the list of renewables, the zone demand is reduced by the amount of power produced by each element of that list. However, in this case, zone demands are considered lesser than renewable output generation and are matched with only this type of power source. The excess of power is transferred to another zone in need.

$$\begin{aligned}&\textit{if}\ \ \text{renOutput}_{u,i} > 0: \\ &\textit{then}\ \text{renOutput}_{u,i} = \min(\text{renOutput}_{u,i} - \text{Load}_{z,i}, \text{transCap}_{i,l})\end{aligned} \quad \text{(Eq18)}$$

Eq18 checks the condition for this transfer. The transmission lines capacity has to be accounted for. The excess power quantity transported must remain under the lines limits between different zones. The demand in the receiving zone is reduced, by the amount of power transmitted.

4.1.6.1.2.2 Define and implement *Utility* function

We use a utility function, which will allow us to sort the conventional units, using the list *commitList*. This sorting is based on the value of the term *unitUtility*. Because this value is linked to costs, the lower it is, the better. The lower this value, the higher the priority of the corresponding unit, in the list. In other word, the unit with the lowest *unitUtility* value is placed at the beginning of *commitList*, making it candidate for the first one to be committed. The operational characteristics of the plants - namely ram ramp rates, minimum up time, and down time - are also taken into account to determine the generation output and when to turn plants ON/OFF.

$$\begin{aligned}&\text{ups} = 0 \\ &\textit{if}\ \ i{=}1\ \textit{and}\ \text{unit}\ \textit{in}\ \text{prvCommitment:} \quad \text{(Eq19)} \\ &\textit{then} \begin{cases}\text{prvComCapacity}_{u,i} \neq 0 \\ \text{ups} = \text{ups} + 1\end{cases}\end{aligned}$$

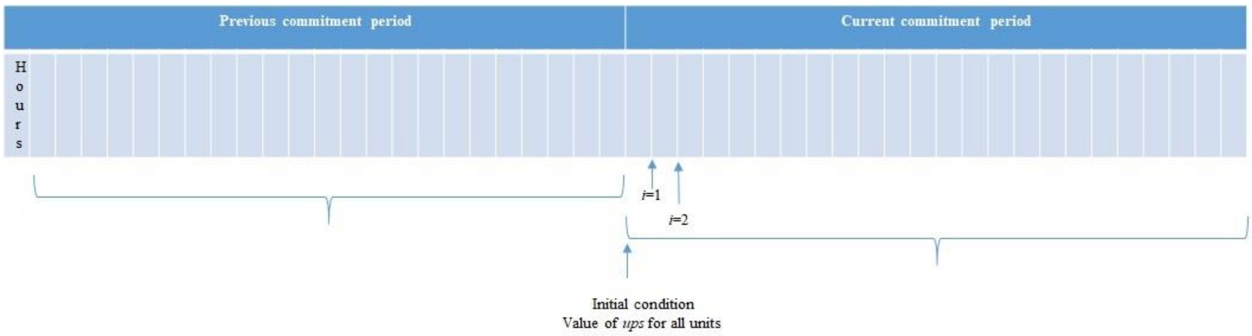


Figure 9: Time horizon for period commitment

Eq19 sets up the initial conditions for the current commitment period. For all units to be committed during this commitment period, we have to look back into the schedule in the previous commitment period to verify their status (Figure 9). The list *prvCommitment* in Eq16 represent the units committed during that period. The term *ups* represent the total number of hours units were last ON/OFF, successively. This count helps decide whether or not, based on minimum up and down times, to commit certain units.

$$
\begin{aligned}
&\textit{if}\;\; i >= 2 \;\textit{and}\; \text{unit} \;\textit{in}\; \text{prevHG}[i-1]: \\
&\textit{then}\begin{cases} \text{downTime}_u \;=\; 0 \\ \text{upTime}_u \;= \text{upTime}_u \;\; +1 \end{cases} \qquad\qquad \text{(Eq20)} \\
&\textit{else}\begin{cases} \text{downTime}_u \;=\; \text{downTime}_u +1 \\ \text{upTime}_u \;= 0 \end{cases}
\end{aligned}
$$

Using Eq20, we track the status of units during the current commitment period. Anytime a unit is ON, the term *upTime* is incremented, and the term *downTime* is brought to 0. If a unit is turned OFF, this time, the term *downTime* is incremented and *upTime* is brought to 0.

$$
\begin{aligned}
&\textit{if}\;\; \text{downTime}_u \;\geq\; 1: \\
&\quad \textit{if}\;\; \text{downTime}_u \leq \text{minDownTime}_u: \\
&\quad \textit{then}\; \text{unitOutput}_i = 0 \qquad\qquad \text{(Eq21)} \\
&\quad \textit{else}\begin{cases} \text{unitOutput}_i = \min\left(\left|\text{downTime}_u - \text{minDownTime}_u\right| \times \text{rampRate}_u \times \text{nomCapacity}_u, \text{nomCapacity}_u\right) \\ \text{unitUtility}_i \;= \text{varCost}_{u,i} - \textit{extra} \end{cases}
\end{aligned}
$$

Eq21 enforces down time constraints. If a unit is OFF and has been in this state for a duration less than its minimum down time, that unit cannot be turned ON. We set its output generation to 0. In the opposite case, the unit may be turned ON, with an output generation constrained by both its ramp rate and nominal capacity. Its output cannot be greater than the nominal capacity.

$$
\begin{aligned}
&\textit{if}\ \ \mathrm{upTime}_u \ \geq\ 1:\\
&\quad \textit{if}\ \ \mathrm{upTime}_u \leq \mathrm{minUpTime}_u :\\
&\quad \textit{then} \begin{cases} \mathrm{unitOutput}_i = \min\left(\mathrm{prvComCapacity}_u + (\mathrm{rampRate}_u \times \mathrm{nomCapacity}_u),\ \mathrm{nomCapacity}_u\right) \\ \mathrm{unitUtility}_i = \mathrm{varCost}_{u,i} - \textit{extra} \end{cases} \quad \text{(Eq22)}\\
&\quad \textit{else}\ \ \mathrm{unitUtility}_i = \mathrm{varCost}_{u,i} + \textit{extra}
\end{aligned}
$$

Eq22 enforces the *up-time* constraints. If a unit is ON, its output generation is also constrained by both its ramp rate and nominal capacity. Its output cannot be greater than the nominal capacity. The unit capacity previously committed is used to compute the capacity to be committed ahead using the ramp rate.

The term *extra*, in both Eq21 and Eq22 is a numerical value, which helps alter the value of *unitUtility* and eventually alternate plants in their order of use. In Eq18 for example, if a unit has been OFF during a time period longer than the *minDownTime*, the value *extra* is added to the variable costs of that unit in such a way to lower its utility value and thus raise its priority order and make the plant available for commitment. Otherwise, the value added raises its utility value and pushes the plant further in the order for selection. In Eq19, if a unit has been ON for a time period lesser than *minUpTime*, its utility value decreases, placing it ahead in the queue, to being committed.

4.1.6.1.2.3 Computation of unit generation capacity

In this section, we describe how to schedule the non-renewable type units, deciding when to turn them ON or OFF. The units are ranked based on their *unitUtility* value.

$$\begin{aligned}
&\textit{if}\ \text{unitOutput}_{u,i} < \text{minPower}_u:\\
&\textit{then}\ \text{comOutput}_{i,u} = (-1) \times \text{unitOutput}_{i,u}\\
&\textit{else}\ \begin{cases}\text{comOutput}_{i,u} = \min\,(\text{unitOutput}_{i,u}, \text{Load}_{z,i})\\ \text{Load}_{z,i} = \text{Load}_{z,i} - \text{comOutput}_{i,u}\end{cases}
\end{aligned} \qquad \text{(Eq23)}$$

Eq23 regulates the use of plants for a given zone. The main constraint examined here is the minimum output generation of units. If units generate less than their minimum required capacity, we attribute a negative coefficient to this value, signaling that the unit in question cannot be committed. When committed, the covered zone load is deducted.

$$\begin{aligned}
&\text{comOutput}_{u,i} = \min\,(\min\,(\text{unitOutput}_i, \text{Load}_{z,i}), \text{transCap}_{i,l})\\
&\text{unitOutput}_{u,i} = \text{unitOutput}_{u,i} - \text{comOutput}_{u,i}\\
&\text{Load}_{z,i} = \text{Load}_{z,i} - \text{comOutput}_{u,i}\\
&\text{transCap}_{i,l} = \text{transCap}_{i,l} - \text{comOutput}_{u,i}
\end{aligned} \qquad \text{(Eq24)}$$

Eq24 regulates the transfer of power across zones. If there is an excess of power in one zone, this excess is transported to another zone, if requested, in order to match demands. The transmission lines capacity constraints are enforced here, making sure the power carried from one zone to the other is not above the lines capacity. The remaining capacity, if any, of units used is computed, and so is the remaining load and line capacity limit.

4.1.6.1.2.4 Commit conventional units

This step consists in committing the units.

$$\begin{array}{l} \textit{if} \;\; \text{comOutput}_{u,i} \; \geq \; 0: \\ \textit{then} \, \text{unit} \; \textit{in} \; \text{commitList}_i \end{array} \quad \text{(Eq25)}$$

$$\begin{array}{l} \textit{if} \;\; \text{comOutput}_{u,i} \; \neq \; 0: \\ \textit{then} \, \text{unit} \; \textit{in} \; \text{prevHG}[i-1] \end{array} \quad \text{(Eq26)}$$

Eq25 shows the condition for a unit to be committed. If the term *comOutput* is positive, the corresponding unit can therefore be committed. It is added to the list *commitList.* This list provides the order in which units are arranged and committed. At the same time, all units that have been used and not necessarily committed are added to the list *prevHG*, tracking when a unit was ON or OFF (Eq26). This tracking is key, as demonstrated in Eq19 and Eq20. If the term *comOutput* is negative, the corresponding unit is ON but cannot be committed.

4.1.6.2. Economic Dispatch

Economic Dispatch (ED) consists in monitoring load and generation, and ensuring balance of supply and load at the current hour. The BAA, which is specific to each balancing area, takes action to ensure and maintain this balance at all time.

The variable O&M cost of generating units is a key factor in deciding which units to dispatch, in order to meet the demand for electricity. Sequentially, plants with the lowest operating costs are dispatched first, and the ones with higher costs are dispatched subsequently as demand is going up. This order ensures lowest generation operation in real time. Given a load profile for a given generation fleet in a given zone, a decision has to be made as to whether to import power or not from other zones without using local units or in complementarity with local units to use only local units and import surplus if applicable or use storage units if available. The order of selection of units for dispatch should differ across balancing areas, as different areas may present differences in renewable and/or conventional source availability, fuel costs, and load patterns. Renewable energy sources, including wind, solar, and hydroelectric, have no fuel costs and present very low operating costs. For this reason, these sources are dispatched first if available. In addition, the economics and technical characteristics of nuclear power plants have made this technology in some countries including the USA almost invariably operate as baseload units at maximum output (IAEA 1987).

The market is set up in such a way that the generating units with the lowest marginal costs enjoy priority of dispatch (Bouckaert and Van Moer 2017). The BAA decides, in real time, the quantity of power each of the available units in its corresponding zone should operate at, considering their respective generating costs and the actual load. The availability of units is derived from the schedule developed during the unit commitment stage. In addition to the use of local generators, power imports/exports are also considered. Zones import power if it is more economically advantageous; that is, buying from another zone is cheaper than using local units or resorting to local storage units. Power is traded at each time step, where zones in deficit request the amount of power needed (MWh) and make offers about how much they are willing to pay ($/MWh). Zones in excess receive offers from all requesting zones and accept the highest bids, as it allows more benefits. This trade is dependent on the transmission network as well. Zones can only trade if (1) there is an existing transmission line between them and (2) the amount to be traded is not more than the capacity limits of the lines.

Our approach is an optimization of the generation dispatch at each time-step (hourly) over a given period. It takes into account the variability injected by renewable sources and power consumption. It also takes into account the transmission lines network and storage. The approach is based on a power market description, consisting of several bidding rounds from different zones where generation dispatch is determined by the operating costs and transmission constraints.

4.1.6.2.1 ED problem formulation

As stated earlier, this model focuses on the units made available during the unit commitment phase to match actual load. The operational constraints namely ramp rates, minimum up/down time, minimum generation output, and planned outage are not taken into account in this model. We posit that these constraints were considered during the unit commitment phase which, as a result, provide to the dispatch operator the list of generating units available in real time.

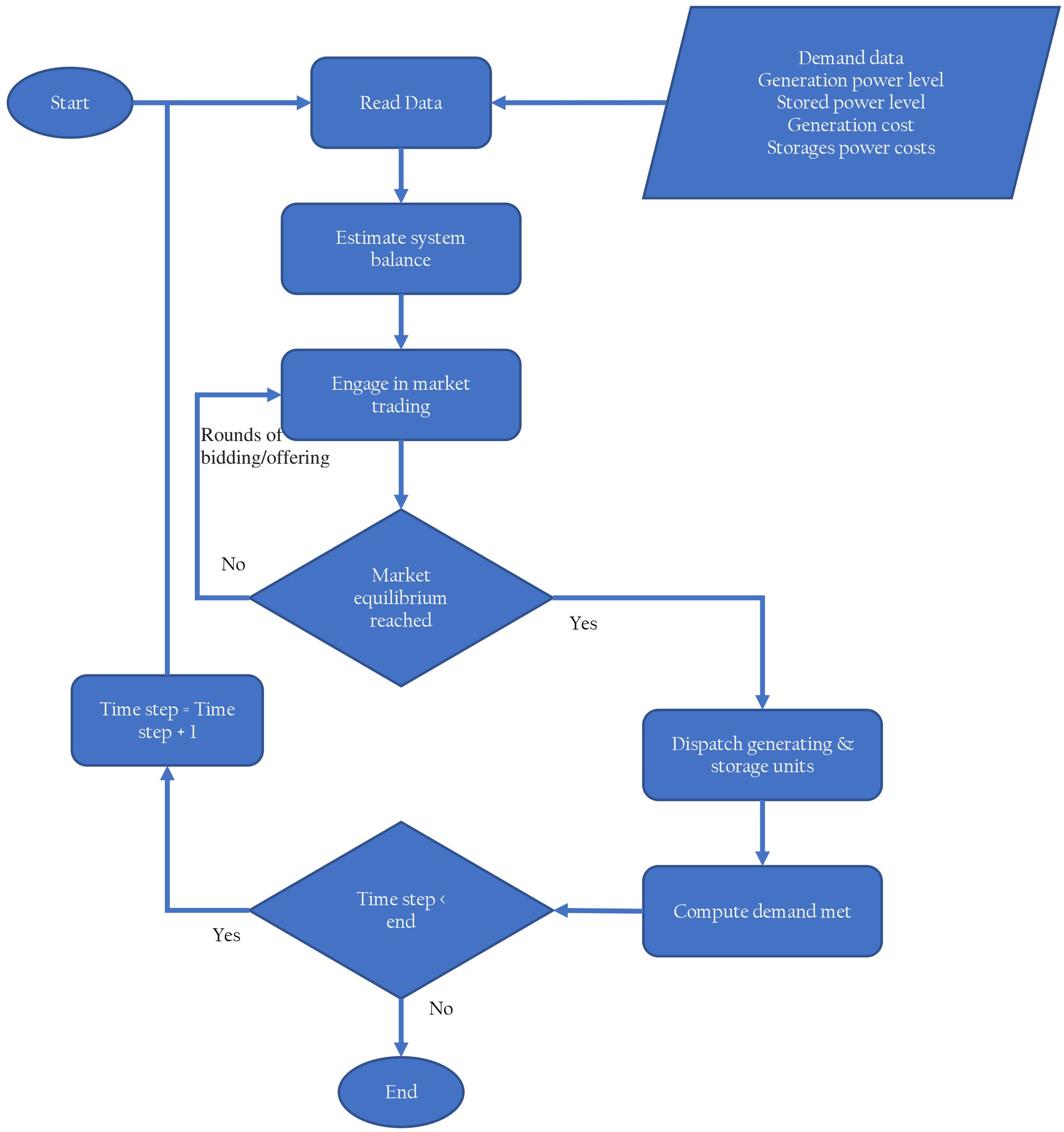


Figure 10: Unit dispatch model process overview.

Figure 10 displays the process followed by the dispatcher model to perform the unit dispatch. The dispatcher receives information from all generators and storage units available in the zone, including generated and stored power levels and generation costs, as well as stored power costs. In addition, it also receives load information, indicating how much demand is needed at a given hour. The dispatcher then compares the overall power quantity and the demand and establishes needs. If there is more demand than supply, the dispatcher initiates power trade with all other dispatchers in the network, requesting the needed quantity of power. Trades between two zones can only take place if they are connected via these lines. Imports may come from multiple zones. In the same way, a zone can export power to several zones during the same hour. The market equilibrium is reached when no more import/export is possible. Once it happens, the dispatcher identifies its trade partners, specifying the amount of power exchanged as well as attached costs. Subsequently, the dispatcher identifies the local generators to be dispatched, as well as the power quantity needed to meet the demand. Finally, the dispatcher assesses the amount of demand which could be covered. This process takes place at each time step (hour) until the length of the simulation run is reached.

4.1.6.2.2 ED modeling

In this section, we describe, in more detail, the steps in Figure 10. Table 7 displays all of the parameters used, and Table 8 displays all the lists, which are the sequence of zones ordered based on their bids/offers. Table 9 displays all the sets used in our method, which correspond to the indices used in variables and equations.

Table 7: List of variables in ED problem

Name	*Description*
demand	Zone demand
deficit	Electricity shortage in a zone
fuelCost	Fuel cost
genOutput	Generator output
genSurplus	Surplus generator output
opCost	Operating costs
powerNeeded	Deficit in power in a zone
powerPrice	Price of electricity in each zone
powerStored	Power stored
powerSurplus	Excess of power in a zone
qtyNeeded	Amount of power needed to cover electricity shortage in zones
qtySupplied	Amount of power supplied to cover electricity shortage in zones
reqTransmitted	Requests of power across zones
storageCapacity	Capacity of storage unit
storageEff	Storage efficiency
totAvailPower	Total generation output in the zone
totDemand	Total demand in the zone
transCapacity	Capacity limit of transmission lines
transLoss	Loss due to transmission
varCost	Variable cost

Table 8: List of all lists in ED problem

Name	
powerShared	List of zones with which to share power
powerSupply	List of all zones in excess offering power
powerSupplyList	List of selected zones in excess from which to request power
rkdPowerSupplyList	List of zones in excess, ranked from highest to lowest bid

Table 9: List of set in ED problem

Name	*Description*
h	Time periods (hour in our case)
l	Transmission lines between zones
r	Trading rounds in the solving loop
s	Storage unit index
u	Power plants or unit index
z	Zone index

4.1.6.2.2.1 Estimate system balance

This phase is composed of two steps, namely (1) aggregate demands and generation output and (2) specify request. The objective is to differentiate zones in excess from zones in deficit in order to define their roles in the market trading.

$$\text{totAvailPower}_{z,h} = \sum_{u} \text{genOutput}_{u,h} \text{ (Eq27)}$$

$$\text{totDemand}_{z,h} = \sum_{d} \text{demand}_{d,h} \text{ (Eq28)}$$

$$\textit{if } \text{totDemand}_{z,h} \geq \text{totAvailPower}_{z,h}$$

$$\textit{then} \begin{cases} \text{deficit} = \textit{True} \\ \text{powerSurplus}_{z} = 0 \\ \text{powerNeeded}_{z,h} = \text{totDemand}_{z,h} - \text{totAvailPower}_{z,h} \\ \text{powerPrice}_{z,h} = \dfrac{\sum_{u} \text{genOutput}_{u,h} \times \text{genCost}_{u,h}}{\text{totAvailPower}_{z,h}} \end{cases}$$

$$\textit{else} \begin{cases} \text{deficit} = \textit{False} \\ \text{powerSurplus}_{z,h} = \text{totAvailPower}_{z,h} - \text{totDemand}_{z,h} \\ \text{powerNeeded}_{z,h} = 0 \\ \text{powerPrice}_{z,h} = \dfrac{\sum_{u} \text{genOutput}_{u,h} \times \text{genCost}_{u,h}}{\text{totAvailPower}_{z,h}} \end{cases} \quad \text{(Eq29)}$$

Eq27 and Eq28 illustrate the first step, as all power generated as well as loads requested within each zone are computed for each hour. Eq29 illustrates the second step. In this step, zones in deficit compute the power quantity needed. Zones in excess, rather, compute the excess power to sell to others and set the price they are willing to sell for.

4.1.6.2.2.2 Engage in market trading

This phase illustrates the import/export of power between zones in the network. The objective is to allow electricity to flow in the network in the least costly manner. All zones are involved in trading as long as they are connected via transmission lines. This phase is composed of three steps: (1) request, (2) analyze, and (3) confirm.

In the first step, a zone in deficit seeks to import power from other zones. It sends the same request to all zones in excess. A zone in excess seeks to export its surplus. It sends the same information to all zones in deficit as well as the costs.

In the second step, a zone in deficit analyzes the offers from all zones, ranking them in a list *powerSupply* (Eq30) from the cheapest to the most expensive. This list also includes the costs of using local generating and storage units. The list is run through, sequentially, until demands of zone in deficit are met. If the zone demand is met before the whole list is run through, the remaining elements of the list are not considered. That is, to these power sources, the zone in deficit sends neither bids nor requests. At that point, each zone in deficit is set on where it is going to import its power from. They then send a list, *powerSupplyList*, to all zones in excess, composed of their name, the quantity they requesting, as well as their bid to acquire the amount of electricity needed.

$$
\begin{array}{l}
\textit{for}\ \text{unit}\ \textit{in}\ \text{powerSupply} \\
\quad \text{totDemand}_{z,h,r} = \text{totDemand}_{z,h,r} - \text{unit.capacity} \\
\quad \textit{if}\ \ \text{totDemand}_{z,h,r} \geq 0 \\
\qquad \text{qtyNeeded} = \text{unit.capacity} \\
\quad \textit{else}\ \text{qtyNeeded} = \text{unit.capacity} + \text{totDemand}_{z,h,r} \\
\qquad \text{totDemand}_{z,h,r} = 0 \\
\quad \text{powerSupplyList.append(\{"bid":powerPrice}_{z,h,r}\text{, "quantity":qtyNeeded, "requester":name\})}
\end{array}
\qquad \text{(Eq30)}
$$

In the third step, the zones in excess receive the requests. Unlike zones in deficit, the zones in excess rank requests (list *rnkpowerSupplyList*) from the ones offering the highest bid to the lowest ones. The objective is to supply power to the zones which offer to pay the most in order to maximize profits in the region. At that point, it confirms to all dispatchers the quantity it will be able to deliver. This quantity does not go over the excess power (if any) it claimed to have at the beginning.

$$
\begin{aligned}
&\textit{for}\ \text{unit}\ \textit{in}\ \text{rkdPowerSupplyList} \\
&\quad \text{powerSurplus}_{z,h,r} = \text{powerSurplus}_{z,h,r} - \text{unit.capacity} \\
&\quad \textit{if}\ \ \text{powerSurplus}_{z,h,r} \geq 0 \\
&\qquad \text{qtySupplied} = \text{unit.capacity} \\
&\quad \textit{else}\ \text{qtySupplied} = \text{unit.capacity} + \text{powerSurplus}_{z,h,r} \\
&\qquad \text{powerSurplus}_{z,h,r} = 0 \\
&\quad \text{powerShared.append}(\{\text{"quantity":qtySupplied, "requester":name}\})
\end{aligned}
\qquad \text{(Eq31)}
$$

An issue may arise. During the second step, when the dispatcher from a zone in need targets where it is going to get its power from, it does not take into account (since it does not know) what other dispatchers are requesting, where they are requesting, and how much they are bidding for it. So, if it turns out it places the lowest bid, it will be the last to be served, as at the third step, requests with highest bids are handled first. This is if there is enough excess power. If not, it receives no power at all. To address that issue, we allow for multiple rounds of bidding/offering between dispatchers, until market equilibrium is reached (Figure 10). That is, until all needed excess power is used to cover any extant deficit. The three steps in the market trading are thus repeated several times/rounds, which take place during the same hour. If during the first round, a zone in deficit does not have its request, or the totality of its request is covered, it can still send the request, or remaining portions of the request during the second round. The process is repeated for as many rounds as needed.

$$\begin{aligned}
&\text{reqTransmitted}_{l,r,h} = \min\,(\text{transCapacity}_{l,r,h}, \text{reqTransmitted}_{l,r,h} \times (1+\text{transLoss}_l)) \\
&\text{transCapacity}_{l,r,h} = \text{transCapacity}_{l,r,h} - \text{reqTransmitted}_{l,r,h} \\
&\textit{if}\ \ \text{transCapacity}_{l,r,h} < \text{transCapacity}_{l,r,h} - \text{reqTransmitted}_{l,r,h} \\
&\textit{then}\ \text{transCapacity}_{l,r,h} = 0
\end{aligned} \qquad \text{(Eq32)}$$

This mechanism requires accounting for the transmission lines. It is critical to make sure that the transmission capacity limits are enforced despite the number of rounds. Eq32 presents these constraints. The amount of power requested from one zone to another cannot exceed the capacity limits of the lines. The transmission losses are also considered. If trading takes place between two zones during a round, the line capacity is updated, indicating the mount of power that can be transmitted through the same line during the following round.

4.1.6.2.2.3 Dispatch power supply unit

This phase illustrates the selection of generating and storage units to dispatch at each time step. Once it is clear for each zone where or if to import/export electricity, the dispatcher can then utilize local generators and storage, based on their costs.

$$\text{opCost}_{u,h} = \text{varCost}_{s,h} + \text{fuelCost}_u \times \text{genOutput}_{u,h} \quad \text{(Eq33)}$$

Eq33 displays the formula of the operating costs of all conventional generating units. Since renewable sources do not use fuels, their operating costs are just the variable costs. Energy storage is an important concept when it comes to power system flexibility and maintaining the balance between the power supply and demand (Amiryar and Pullen 2017). Just like the generators, the storage units belong to zones and are able to store power only when there is more supply (especially from intermittent power plants production, namely wind power, tidal power, solar power, etc.) than demand. However, power cannot be stored beyond the capacity of the storage (Eq34).

$$\text{powerStored}_{z,h} = \min\left(\text{storageCapacity}_{s,z}, \text{powerStored}_{z,h} \times \text{storageEff}_{s,z}\right) \quad \text{(Eq34)}$$

Storage is valued for its ability to rapidly begin discharging power to the grid, as opposed to fossil fuel sources, which tend to take a bit longer for ramping up. This quickness in response is important as it helps ensure grid stability when there is a drastic change in demand or renewable generation output. Because the energy stored is more often than not from renewable sources, considering only variable operating costs would mean that the storage would always have the lowest costs, since there are no fuel costs. Going in this direction would imply that the storage would immediately be emptied during the subsequent time unit. Instead, the cost for dispatching should reflect a *value*, as suggested by Svendsen and Spro (2016), which would depend on the filling level and time. This would allow storage units to be dispatched in an effective and reasonable manner. According to Svendsen and Spro (2016), if the storage is near its full capacity, the *value* should be low, simply because the storage is close to its limit, which may happen mostly at night. If the storage is close to being empty, the *value* should be high, so as to not use the stored power prematurely.

In our model, we consider storage units just as generators waiting to be dispatched if this is the least expensive option. Their operating costs are updated when extra power is stored (Eq35). These costs vary based on the quantity of power stored in the previous time step and the excess power added at current time.

$$\text{opCost}_{s,h} = \frac{\sum_{u} \text{genSurplus}_{u,h} \times \text{opCost}_{u,h} + \sum_{s} \text{powerStored}_{s,h-1} \times \text{opCost}_{s,h-1}}{\sum_{u} \text{genSurplus}_{u,h} + \sum_{s} \text{powerStored}_{s,h-1}} \quad \text{(Eq35)}$$

Because the algorithm allows units to be dispatched solely based on their operating costs, and across multiple zones, there is no room for curtailment. A surplus of generation output from renewable sources is carried over transmission lines. If it is enough to cover the demands, no conventional source is brought on. Otherwise, the conventional sources cover the remaining demand.

4.1.6.2.2.4 Compute demand met

This is the last phase of the dispatch unit algorithm. At this point, we assess the amount of demand that can be covered.

4.2 Model Specification

This research formally sets forth an architecture for *Spark!*. The model is designed on the premise that complex systems, like power grid systems, can be modeled in a modular and layered fashion, in which systems specification can be built on top of previously verified components (Zeigler 1976). Each component —*generators*, *transmission lines*, *loads*, *dispatchers*, *unit commitment,* and *storage*— is modeled as an *atomic* DEVS model. Their behavior changes due not only to internal mechanisms but also to external inputs. The *generators*, *loads*, *dispatchers*, and *storage* models are located at the *zone layer* of the system. The connections between *generators*, *loads*, *storage* models and *dispatcher* model form the zone, which is built as a *coupled* DEVS model. The connections between the *zone*, *transmission lines* and *unit commitment* models form the *inter-zone* model, which is also a *coupled* DEVS model. This model is located at the *inter-zone layer* of the system. Figure 11 illustrates these layers. In this figure, *coupled* DEVS models are displayed as parallelograms while *atomic* DEVS models as cylinders.

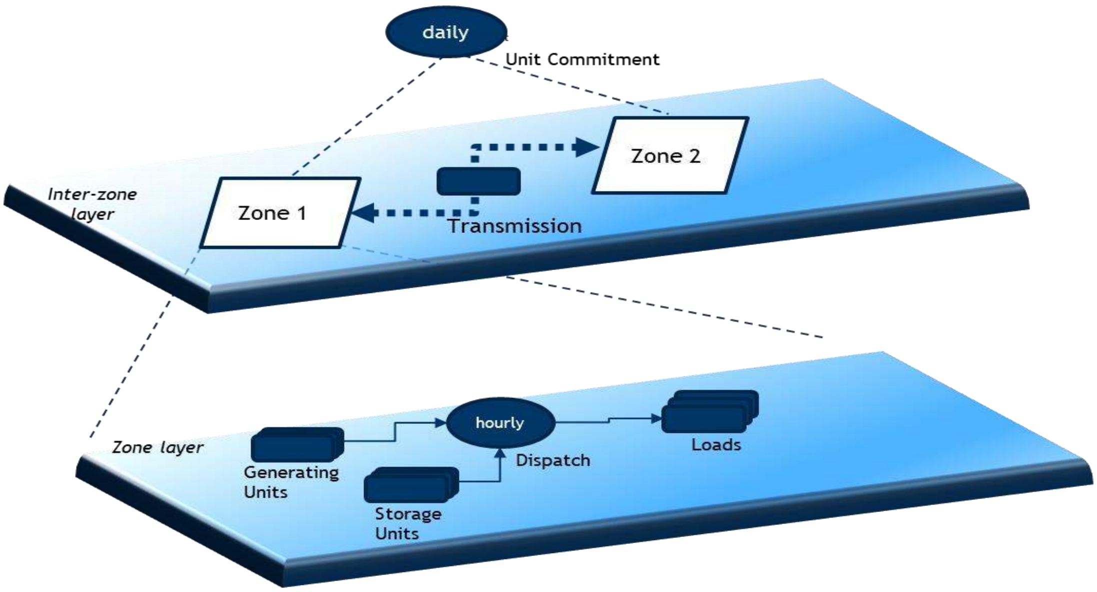


Figure 11: Hierarchical representation of the electricity system

4.2.1 Atomic models

4.2.1.1 Modeling *Unit commitment* component

This model represents the entity responsible for the scheduling of on/off decisions and output levels for power plants over a given time horizon (Dentcheva, Gollmer et al. 1997). The model has one output port, and no input port.

O_{uC}/G: Output port that sends messages to *Generators* models. These messages indicate scheduled power generation over a specified commitment period.

4.2.1.2 Modeling *Generator* component

This model represents electricity generating plants, or power plants. They produce electricity. Each of them has various characteristics, namely a minimum uptime (minimum time the plant has to remain ON), minimum downtime (minimum time the plant has to remain OFF), ramp rate (time it takes for the plant to reach its nominal capacity), minimal capacity (minimum capacity the generator must produce), and nominal capacity. The model provides the dispatcher with the amount of power available and the cost it will charge for usage hourly. It then updates its remaining capacity when informed by the dispatcher about the actual power quantity needed at this hour and stores its unused capacity. These models have two input ports and two output ports.

O_G/D: Output port that sends messages to the *Dispatcher* model. These messages indicate the available power capacity that can be used to meet the demand, at a specific time unit.

O_G/S: Output port that sends messages to the *Storage* model. These messages indicate the power in excess.

I_G/uC: Input port that receives messages from the *unitCommitment* model. These messages indicate to each generator the quantity of electricity to be used throughout the commitment period.

I_G/D: Input port that receives messages from the *Dispatcher* model. These messages indicate the proportion of electricity deemed necessary to meet the demand expressed.

4.2.1.3 Modeling *Loads* component

Loads model represents demand expressed by consumers. They request electricity. In our case, this model includes all types of electricity demands, namely residential, commercial and industrial. These models have one input port and one output port.

I_L/D: Input port that receives messages from the *Dispatcher* model. These messages indicate the quantity of demand met based on the total supply and the total demand expressed.

O_L/D: Output port that sends messages to the *Dispatcher* model. These messages indicate the electricity needed for consumption.

4.2.1.4 Modeling *Dispatcher* component

The *Dispatcher* model represents entities responsible for ensuring balance between power supply and demand every hour. The goal is to satisfy the overall demand in the least expensive way possible. This model has four input ports as well as four output ports.

O_D/L: Output port that sends messages to the *Loads* model. These messages indicate the amount of demand which can be satisfied.

O_D/G: Output port that sends messages to the *generators*, indicating the amount of power to be used to meet the demand.

O_D/TL_{resp}: Output port that sends messages to other *Dispatcher* model through transmission lines, indicating the amount of additional power available or not, in a given zone.

O_D/TL_{info}: Output port that sends messages to other *Dispatcher* models. These messages indicate either the surplus amount of power available to spare or the deficit and need in power.

I_D/L: Input port that receives messages from the *Loads* model, indicating the total demand in electricity.

I_D/G: Input port that receives messages from the *generators* model. These messages indicate the list of all power plants as well as their available capacity.

I_D/TL_{info}: Input port that receives messages from the *Dispatcher* model, indicating the extra amount or deficit of power.

I_D/TL_{resp}: Input port that receives messages from other *Dispatcher* model. These messages specify the response from other dispatchers.

4.2.1.5 Modeling *Transmission Lines* component

Transmission Lines are entities responsible for carrying high voltage power from one point to another. In our model, they are related to the dispatchers of each zone. These models have two input ports and two output ports.

O_{TL}/D_{info} and O_{TL}/D_{resp} are output ports through which messages are transmitted to the *Dispatcher* model. These messages indicate, as explained in the previous section, excess/deficit information and responses, respectively, to alternative dispatchers.

I_{TL}/D_{info} and I_{TL}/D_{resp} are input ports through which messages are received from *Dispatcher* model.

4.2.1.6 Modeling *Storage* component

Storage behave as electricity generating plants. They produce electricity that was stored at an earlier time. These models have two input ports and two output ports.

I_S/D: Input port that receives messages from the *Dispatcher* model. These messages indicate the quantity of power requested and used by the *dispatcher*.

I_S/G: Input port that receives messages from the *Generator* model, indicating the excess or unused power in the *Generator,* which needs to be stored for later usage.

O_S/D: Output port that sends messages to the *Dispatcher* model. These messages indicate the available quantity of electricity for usage.

4.2.2 Coupled models

4.2.2.1 Modeling the *zone* layer

The *zone* layer is a coupled model, composite of *generators*, *storage*, *loads,* and *dispatcher* atomic models. These components are connected via an internal coupling; that is, the component outputs are directly linked to other component inputs. This layer captures the information exchange between those elements, highlighting the activities at the operational level. These couplings are represented by blue arrows in Figure 12. This model also captures the connections between components (the ones mentioned above) and the zone model ports. These connections are made via both external input coupling, with links between the model external inputs and component inputs and external output coupling, with links between component outputs and the model external outputs. The model captures the exchange of information between dispatchers in different zones. This communication is critical, as zones may be in excess and exporting power or in deficit and importing power. As indicated earlier, this communication takes place between dispatcher in each zone.

4.2.2.2 Modeling the *inter-zone* layer

The *inter-zone* layer is also a coupled model, composed of zones coupled models, *Transmission Lines* atomic model and *unitCommitment* atomic model. These models are connected via internal coupling, with each of these components linked to one another. This model highlights the transfer of information between zones. These couplings are represented by green and yellow arrows in Figure 12.

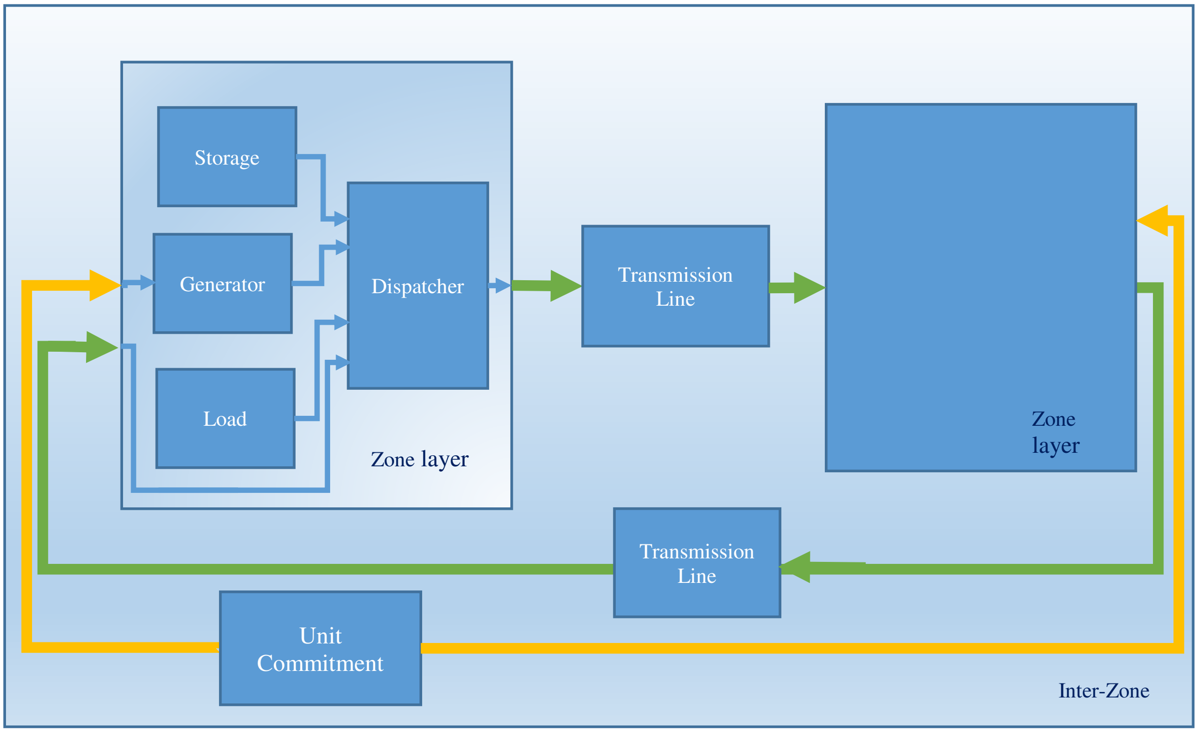


Figure 12: DEVS hierarchical coupling of the electricity system

4.3 Model Implementation

The model is developed using the DEVS formalism, and run on PythonPDEVS, which is a distributed Parallel DEVS simulator (Van Tendeloo and Vangheluwe 2015). The simulator computes the next state (state transition) of each component until termination conditions are met. These changes consist of sequential phases, namely the (1) computation of atomic DEVS models whose internal transitions are imminent, (2) execution of the resulting output function, (3) mapping of output ports to input ports by executing the transfer functions, (4) determination of the type of transition to execute, be it internal or external, depending on the atomic DEVS model being imminent and/or receiving input, (5) execution in parallel, of all enabled transitions, and (6) computation of remaining time before next internal transition for each atomic DEVS model (Van Mierlo, Van Tendeloo et al. 2015).

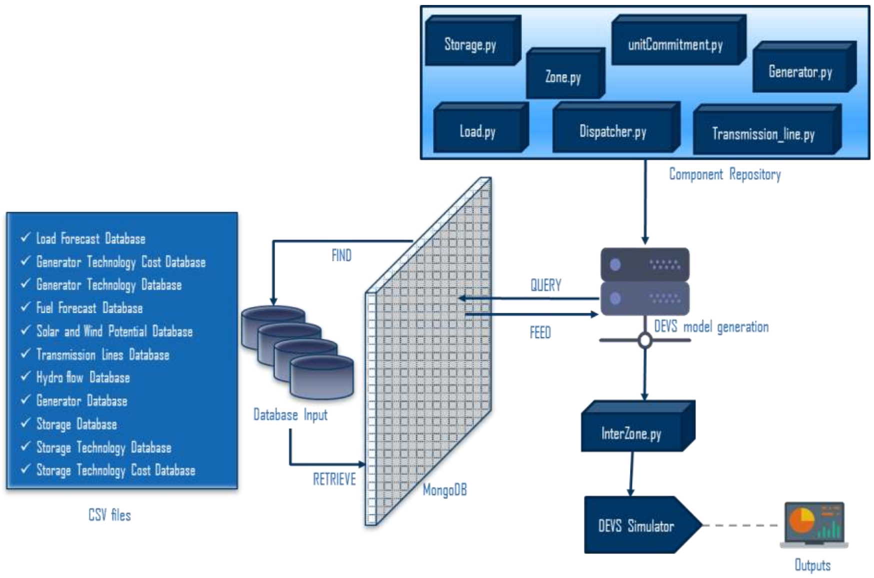


Figure 13: Model Architecture implementation

An overview of the model implementation is displayed in Figure 13. The component repository is composed of *atomic* and *coupled* DEVS models and described by Python® scripts. Instances of these different models are generated based on the availability of data. We use PyModM, a MongoDB module built on top of the Python PyMongo module to access data saved in a MongoDB database. We connect to a locally hosted MongoDB database holding collections with documents, specifying values of varying types needed to feed the DEVS model generation. Data are retrieved from CSV files containing information regarding the attributes of the models to be created. For example, for the load DEVS *atomic* model to be created, information fed to the model generation needs to include the quantity, the type, the location, the season, and the year at which the demand for electricity was requested. The DEVS model generator creates a grid simulation by parameterizing and interconnecting instances of generic Python® classes available in the repository. The grid generated is then simulated via the DEVS simulator.

4.4 Model Input and Output

4.4.1 Model input

In this section, we define all input variable necessary for the model to run. Several database are used, where the model get information from. The data vary from season to season, and zone area to zone area.

Load Forecast Database: Includes data about the power demand per consumer type, geographical zone and year. The different types considered here are residential, commercial, and industrial sectors. This distinction is made given the different patterns of consumption. The residential sector refers to an energy-consuming sector that consists of private households. Commonly, we can think of space and water heating, air conditioning, lighting, refrigeration, cooking, etc. as main sources of energy use. The commercial sector refers to consumption by nonmanufacturing establishments or agencies mostly involved in the sale of goods or services (EIA 2015). Examples would be hotels, restaurants, schools, government buildings, etc. The industrial sector refers to consumption by manufacturing establishments.

Generator Technology Cost Database: The forecast of operating costs; that is, expected fixed and variable operating and maintenance (O&M) costs (excluding fuel costs) for the technologies considered are provided in this database. This is a time series that will include for each technology and each year, the O&M costs of the technology. The fixed O&M costs referred to here are mainly planned maintenance and equipment costs, which vary with the plant size. The variable O&M costs are composed of outage maintenance (forced outage), consumables maintenance (equipment repair) and water supply costs (cost of providing cooling water for plant operations) (Rhyne 2015). Startup and shutdown costs are (costs associated with turning units on and off, respectively) also included in this database.

Generator Technology Database: This database indicates the specifications of the technology used by the generators. We use data regarding estimated lifetime, the heat rate, forced and planned outage rates, years of service, a minimum uptime (minimum time the plant has to remain ON), minimum downtime (minimum time the plant has to remain OFF), ramp rate (time it takes for the plant to reach its nominal capacity), minimal capacity (minimum capacity the generator must produce), and whether or not this technology is committable. Technologies considered are, among others, wind, solar, coal, gas, geothermal, nuclear, biogas, biomass, oil and hydroelectric.

Fuel Forecast Database: The forecasted cost of all fuels. Fuels considered are oil, coal, gas, nuclear, biomass, biogas and petroleum.

Solar and Wind Potential Database: A geocoded database that contains the potential for solar (exposure) and wind production (wind speed) for each geographical area covered by the model.

Transmission Lines Database: This database provides a list of all available high power lines. The information includes the remaining expected life of the lines, the losses, the associated costs as well as the lines capacity. The database indicates the origin and destinations of all the transmission lines.

Hydro flow Database: This database provides information regarding heads and flows in dams. Heads are change in elevation, between the upper and lower reservoirs. Flow is the speed at which water is flowing.

Generator Database: Data regarding the generating units in the power system network are included. More specifically, we have the maximum capacity, name, and technology used for power generation. The location for each generator is also indicated, as well as the year it was put in service.

Storage Database: This database is similar to the Generator Database, providing the same type of information, but in this case for storage units.

Storage Technology Database: In this database, we have the storage efficiency (percentage of power which can be retrieved, out of what was stored) and discharge rate (rate at which the electricity is retrieved for usage), estimated years of service, as well as forced and planned outage rates. Technologies include mechanical (pumped-hydro, compressed air, etc.), electrical (capacitor, supercapacitor, etc.), electrochemical (flow battery, solid state battery, etc.), etc.

Storage Technology Cost Database: This database includes expected fixed and variable O&M costs for the storage technologies considered.

4.4.2 Model output

The output represents the results of the model, after running some experiments. In our case, we consider the measurements of the economic, environmental, and operational performance. We store these measurements in the following databases.

Operational Performance Database: This database stores the computed operational performance of the power utility from the simulation. Information such as reliability of the power supply is also stored. In addition, we compute generators utilization rate, the transmission line utilization rates, and the storage utilization rates per zone as well as for the whole grid.

Economic Performance Database: This database stores the computed economic performance of the power utility. Information such as the fixed costs, capital costs, and O&M

costs as well as revenues are stored. The model computes also the profit/loss. All these results are computed both at the generator level and grid network level. The electricity price per zone is also stored.

Environmental Performance Database: This database stores the computed environmental performance of the power utility. The quantity of CO_2, NO_x, SO_2 emissions per power unit and per zone as well as in the whole grid network are stored in the database.

An important feature is the ability to display these outputs both at the zone and network levels. Because of its architecture, performances can be computed for every single generating unit, at each time unit, and also for the whole grid. The user can thus get a sense of what is happening at the zonal level and how it translates to the network level and vice-versa.

4.5 Model Assumptions

In this section, we list all assumptions made in the model.

- We consider overnight costs, assuming the cost of a construction project incurs no interest, as if the project was completed "overnight." This is a quick and simple way to compare the costs of building different types of electrical plants - and ultimately, compute the total costs of operating them - after each run. This is a hypothetical scenario because a plant can obviously not be constructed in one night. We consider this option to evaluate the cost of a plant if it were built right away with current prices and without taking into account the time it would actually take and how prices would rise over time.
- A reserve-margin constraint of 10% has been imposed in the grid. This choice is motivated by the study performed by IRENA (2013), for the year 2010, which considers the

same value. Only conventional energy sources are considered to contribute to this requirement. This is because renewable sources cannot be committed and scheduled ahead of time.

- The load forecast error is assumed to be uniformly distributed. Under a uniform distribution, the sets of variables all have the exact same possibility of happening. In choosing this distribution, we sought to have the same chances of error at all time units (here, hour). This way, there is statistically no chance to have a significantly important gap (difference between real load and forecast) at some time of the day versus other times.

- Based on the input database, the model computes the limits of deployment and output characteristics of wind, solar, and hydropower technologies. Our model relies on mathematical models used in other peer-reviewed studies to estimate the generation quantity. For wind technology for example, we resort to the Weibull probability density function (PDF), which has mostly been used to fit wind speed distributions for wind energy applications (Carrillo et al. 2014). Once the wind speed distribution is estimated, we also determine the power curve, which is done using a function defined in three regions (Cetinay et al. 2016). In order for the wind turbine to start generating power, wind speed must be greater than the cut-in speed v_{in}. Below this value, there is no power output. Similarly, the wind turbine stops operating at a higher speed than the cut-off speed v_{off}. This is to prevent damage. Power is only generated in between v_{in} and v_{off}, with consideration of the rated speed v_{rated}, the speed at which the maximum power output of the wind turbine is reached and generated before reaching v_{off}.

- The transmission system is modeled as a simple transportation model. Power shared between areas or zones in the network via transmission lines is only constrained by the capacity of those lines. This is in alignment with the level of abstraction of *Spark*!, which does not consider power flow principles and electrical components.

- The transmission loss is assumed constant throughout the scenario run. Normally, the losses vary, depending on specific conductors, the current flowing, and the length of the transmission line (Jackson et al. 2015). However, because our model has a higher level of abstraction, current and electric components are not captured.
- A power plant is equivalent to a generator, or a generating unit. This assumption is also justified by the model level of abstraction.
- Plants are assumed not to undergo maintenance or suffer breakdown. Forced and planned outages are not considered in the unit commitment and dispatch processes.

With the last assumption, we eliminate all errors in forecast and planning caused by planned and forced maintenance. Plants and transmissions are deemed in perfect operating condition at all times during the whole scenario. The other assumptions are justified by the model level of abstraction and techniques used in peer-reviewed research addressing integrated resource planning issues.

CHAPTER 5

VERIFICATION & VALIDATION

This section describes the methods used to validate and verify the model used in this study. First, we present the verification process. The validation process is presented later.

5.1. Verification

Verification consists in determining whether or not the implemented model is consistent with its specification (Sanders, 1996). It checks for transformational accuracy, ensuring that the transformation of the conceptual model into an executable one is accurate enough with respect to the model's design specification. According to Mikel (2010), questions to be answered during verification include:

- Does the program code of the executable model correctly implement the conceptual model? For verification, we use the Control Analysis method (Sargent 2004), checking state transitions takes place the way it is supposed to.

Control Analysis - State Transition Analysis: This technique is conducted to check state transitions and conditions prompting them. This technique requires the identification of all possible states the model execution goes through, the specification of state transitions, and how they match with the system requirements. As we conduct the model verification, several questions need to be (and were) answered:

- Have all states been defined? Yes, they have, and they match the functional requirements of the real system (see Section 4.1.1. for system requirements).
- Can all the states be reached? Yes, they can, as all transitions (both internal and external) were tested.

- Does each state respond properly to all possible conditions? Yes, they do, as all corresponding output functions were triggered, and appropriate output sent to other atomic DEVS models.

We were able to trace all state transitions for all atomic DEVS models in our model and compare them with the conceptual model. Trivial examples were also used where we could ensure that state transitions provide expected behavior. For example, we considered a grid with two BAs and later three BAs, three generating units each and different load profiles, for two cases: one with a transmission network and the other with none. We could check (1) that state transitions occurred as expected, and they trigger corresponding behaviors, (2) that less expensive generating units were dispatched first before more expensive ones, (3) that power was not exchanged in the case of nonexistent transmission network, (4) that in the case of existing transmission network, the transmission capacity was always respected, and (5) that market dynamics takes place as expected, with bid-based transactions.

Figure 14 below displays state transition of the *Load* atomic DEVS model, representing the residential demand in Mali. In initial conditions, at time 0, the state is *idle*. An internal transition is scheduled at the same time unit, during which the model evolves to state *request*. In this state, the model is expected to request the demand needed (residential). The output function is thus triggered, sending a message to the Dispatcher atomic DEVS model and specifying this need through port DemandToDispatcher. The next internal event happens with state transition from *request* to *wait*. The model stays in this state for INFINITY, meaning, no state transition can happen without an (external) input from another atomic DEVS model. Once such an input is received, the external transition function is triggered, prompting a transition to state *advance*. The input must be from Dispatcher atomic DEVS model, specifying the amount of demand met.

The next event is an internal transition, scheduled to take place at the next time unit, with the model transitioning to state *request*. The cycle repeats.

```
_  Current Time:       0.00 ________________________________________

 INITIAL CONDITIONS in model <interZone.mali.residential>
        Initial State: idle
        Next scheduled internal transition at time 0.00

 INTERNAL TRANSITION in model <interZone.mali.residential>
        New State: request
        Output Port Configuration:
                port <DemandToDispatcher>:
        Next scheduled internal transition at time 0.00

  INTERNAL TRANSITION in model <interZone.mali.residential>
         New State: wait
         Output Port Configuration:
                 port <DemandToDispatcher>:
                         {'name': u'residential', 'quantity': 86.37179605274245}
         Next scheduled internal transition at time inf

 EXTERNAL TRANSITION in model <interZone.mali.residential>
        Input Port Configuration:
                port <SupplyFromDispatcher>:
                        {u'residential':  16.5834645903095, u'industrial': 119.2017461724335, u'commercial': 75.21296240761653}
        New State: advance
        Next scheduled internal transition at time 1.00

_  Current Time:       1.00 ________________________________________

  INTERNAL TRANSITION in model <interZone.mali.residential>
         New State: request
         Output Port Configuration:
                 port <DemandToDispatcher>:
         Next scheduled internal transition at time 1.00
```

Figure 14: State transition of residential type load atomic DEVS model, in Mali

5.2. Validation

Validation consists in determining the level to which the model is an accurate representation of the real system (Sanders 1996). It checks for representational accuracy, ensuring that the representation of the real system in a conceptual one and that the results produced by its execution are accurate enough with respect to its intended uses. According to Mikel (2010), questions to be answered during validation include:

- Does the conceptual model correctly represent the real system?
- How close are the results produced by the executable model to the behavior of the real system?

The main function of the model is long term energy planning while ensuring reliability of the system in the short term. Two critical operations are the unit commitment and economic dispatch phases (see Sections 4.1.6.1 and 4.1.6.2.). The unit commitment phase consists in scheduling the ON/OFF times of plants ahead of time in such a way to minimize the costs associated with hourly generation (Jabr 2013). The economic dispatch phase consists of monitoring load, generation, and ensuring balance of supply and load in real time. For the purpose of our study, we deem our model valid if it performs those operations with good accuracy.

For validation, we use 3 methods, namely functional testing, face validation and graphical comparison (Sargent, 2004).

Functional Testing: This technique is conducted to verify and validate the input-output transformation of the model. The emphasis is placed not on the mechanisms in models but, rather, what is produced as output given a set of input.

In this case, our unit commitment algorithm is used on a benchmark case which has been widely researched in the literature, with 24-hour load profile and a 10, 20, 40, 60, 80, and 100 generating units setting (Kazarlis et al., 1996). We compare the results in terms of total generation costs derived from generating unit commitment scheduling between Delarue, et al.

(2013)'s EPL (extended priority list) model implementation and also Carrión and Arroyo (2006)'s MILP (Mixed-integer linear programming) implementation (Table 10).

Table 10: Total costs of scheduling and differences between our developed method, EPL algorithm and the MILP model.

# units	Total cost ($)			Difference	
	EPL	Our method	MILP	EPL	MILP
10	563,977	564,638	563,938	0.12%	0.12%
20	1,124,481	1,155,768	1,125,721	2.71%	2.60%
40	2,246,926	2,310,738	2,246,243	2.76%	2.79%
60	3,366,240	3,514,932	3,367,262	2.84%	4.20%
80	4,489,342	4,665,359	4,488,560	3.77%	3.79%
100	5,609,109	5,872,037	5,609,210	3.92%	4.48%

The differences in results may be explained by the heuristic used in our algorithm (see Section 4.1.6.1.), which performs plants scheduling based on usage history and current need, without look-ahead mechanism. Units are thus (un)committed to cover demands at the present hour without considering needs at next hour and associated startup/shutdown costs. These differences in results seem to grow as the number of units increase but stabilize.

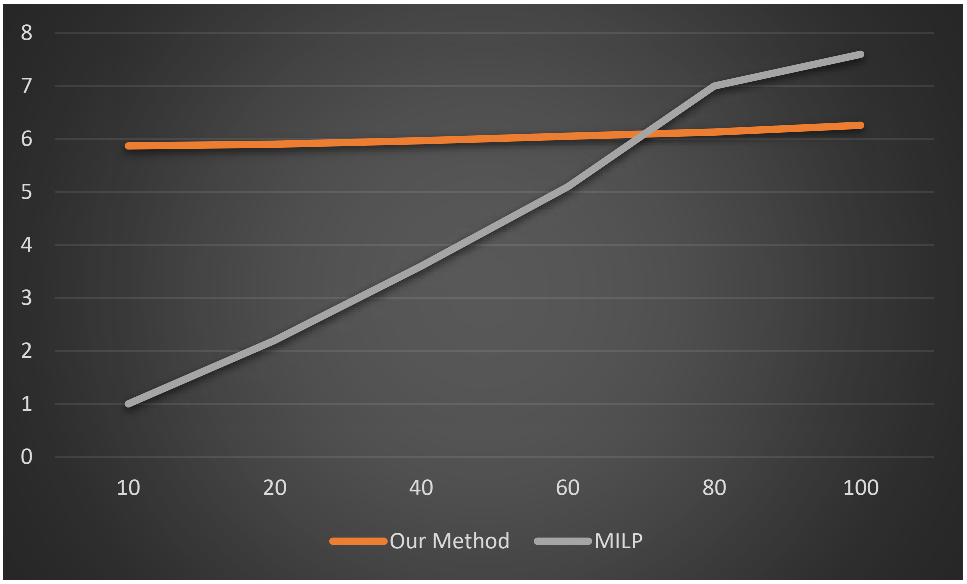


Figure 15: Difference in time (second) computation between our method and MILP

Also, what is lost in accuracy is won in time execution. Looking at Figure 15, we notice that the computation time in MILP tends to grow linearly with the number of plants considered, while our method offers a less steep slope with a seemingly constant value. This is a good advantage over MILP, especially now that power grids are extending in scales. Faster methods providing near-optimal solutions are thus preferable.

As it can be seen, our method turns out to be highly effective, with solutions which are very close to optimal. Our algorithm offers solutions less than 5% off the optimal one with higher scalability and faster implementation, which is quite satisfactory for our purpose and gives us good confidence regarding the credibility of our results.

Face validation: This technique is conducted to compare model and system behaviors under identical input conditions. This assessment is done by subject matter experts or people knowledgeable about the system under study, subjectively judging the reasonableness of the model, its assumptions, and its outputs.

In this case, the economic dispatch phase is tested. The set of experts relied on are professionals working for Dominion Energy, an American power and energy company supplying electricity in parts of Virginia and North Carolina and natural gas to parts of West Virginia, Ohio, Pennsylvania, and eastern North Carolina. These experts were able to provide insights about what a power grid is and how it works at the strategic level. Based on their suggestions, we were able to identify key components of the system, specify the relationships between them, and conceptually design the model. In addition, using data provided by them, we were able to run scenarios and present results, including plants dispatch, usage rates and load balancing, which were thought reasonable under the observed conditions.

Graphical Comparison: This technique is conducted to compare the graphs of values of model variables over time with the graphs of values of system variables and check for similarities.

Considering again the study conducted by IRENA (2013), we compare graphs of generation mix in the WAPP grid for the year 2010. This scenario simulates the West African grid in the state it was at that year with existing plants, transmission networks, and load profiles. We compare our results with the ones obtained in the study at year 2010. Figure 16 displays the generation mix for year 2010 in the whole network, both from the WAPP study and *Spark!* Figures 17 and 18 display the generation mix for different countries, namely Senegal, Nigeria and Ghana. As shown in the figures, our model turns out to be very accurate, with very minor differences.

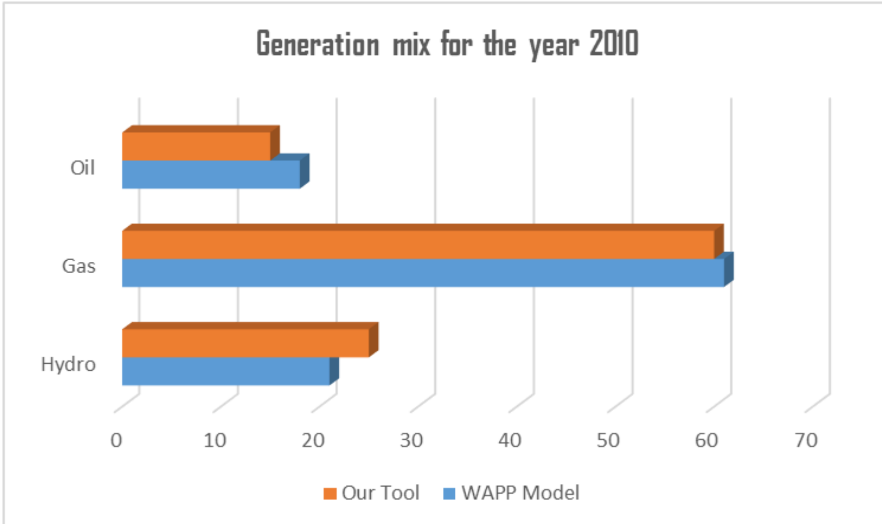


Figure 16: Generation mix for the year 2010.

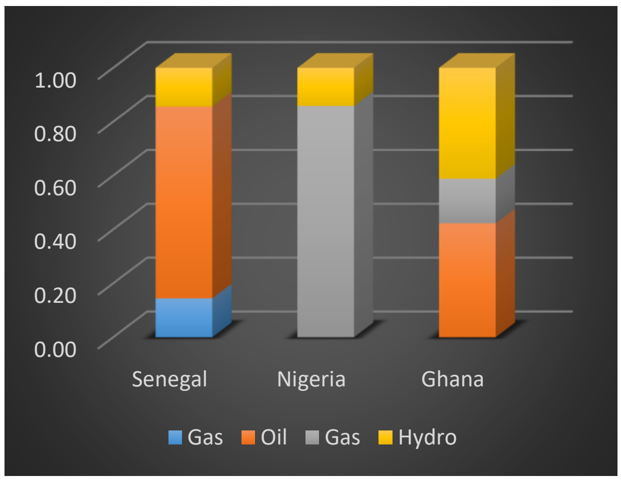


Figure 17: Generation mix 2010, by *Spark!*

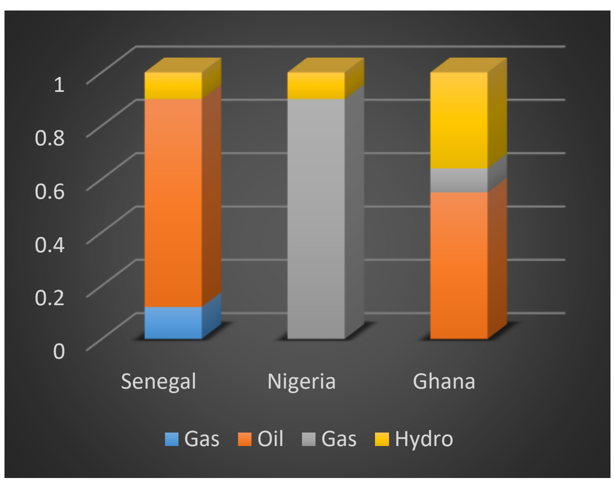


Figure 18: Generation mix 2010, by WAPP

CHAPTER 6

CASE STUDY

For experiments, we choose the West African Power Pool (WAPP), which is composed of ECOWAS (Economic Community of West African States), namely Burkina Faso, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo and Benin, as case study. This part of the world offers a wide variety of energy sources, including important solar energy and wind potential, hydro, coal, gas, and oil as well as biomass (Hermann, Miketa et al. 2014). Those potentials are enormous for countries in this region, yet no considerable investment in energy infrastructure has been made (Vilar 2012). The power network is still underdeveloped and inadequate, offering very limited access to electricity (Ouedraogo 2017). We feel this is a good case to conduct our study, as this is a region in urgent and critical need to improve electricity supply, distribution, and transmission in order to better energy access for its increasing population and also offer avenues for economic growth (Legros, Havet et al. 2009).

Data used in this study are retrieved from the study conducted by IRENA (2013). They include demands, generation fleet, and renewable potential data, for the year 2010. The model used in their study is MESSAGE, to help investment alternatives via various scenarios, and assess economic, environmental, and social implications of a given investment path. Scenarios were run from year 2010 to 2030.

6.1. Case 1: Grid Evolution and Performance

In this case, we analyze associations between grid architectures and performances. The different grid architectures are obtained via the generative method described earlier, in Section 3.2 and *Spark*! The initial grid considered here is the WAPP in year 2010, following the IRENA study. This grid is simulated over 20 years (2010-2030), and the grid architectures generated at the end of this run are the ones of interest. Once obtained, we run a correlation analysis. The dependent variables are metrics that measure the grid performance, namely *reliability*, *affordability,* and *CO_2 emissions*. The independent variables are architecture metrics, namely *density*, *degree centralization*, *clustering,* and *modularity*.

6.1.1 Correlation Analysis

In this section, we present the results of the correlation tests. A sample size of 32 points was used for this analysis (see Section 3.2.2. about the sample size). Table 11 shows all 32 points, describing the grids performance measurements and architecture features. Two types of correlation tests are conducted. At first, a univariate analysis by Pearson's correlation is conducted, where each of the dependent variable is tested against each independent variable. Then, a multivariate analysis by Pearson's correlation is conducted, where combinations of dependent variable are tested against each independent variable. These correlation tests are conducted considering a confidence interval of 95%.

Table 11: Grids performance and architectural features

Density	Modularity	DegreeCentralization	ClusteringCoeff	Reliability	CO2Emission	Affordability	DegreeCent
0.214286	0.381009	0.095238	0	0.922889	176145.3	26711000	0.095238
0.576923	0.01272	0.106061	0.056057	0.670002	199979.5	2994708	0.106061
0.24359	0.37895	0.5	0.01674	0.925238	179025.4	26666405	0.5
0.628205	0.012661	0.143939	0.05444	0.663851	199678.4	2934186	0.143939
0.269231	0.392935	0.469697	0.001286	0.926256	164832.9	26022687	0.469697
0.576923	0.016359	0.204545	0.048389	0.669438	199609.4	26147645	0.204545
0.410256	0.392848	0.401515	0.011613	0.928746	184831.4	2641242	0.401515
0.641026	0.055443	0.227273	0.041561	0.665635	199762.5	2859591	0.227273
0.181818	0.378266	0.654545	0.023341	0.921525	179041.1	26608770	0.654545
0.615385	0.031575	0.257576	0.055435	0.664569	197829.4	3015088	0.257576
0.371795	0.378776	0.348485	0.018667	0.925221	197232.2	25008917	0.348485
0.576923	0.050816	0.204545	0.045213	0.648814	198569.2	2767006	0.204545
0.320513	0.373216	0.409091	0.017874	0.928569	153515	28322666	0.409091
0.692308	0.056956	0.265152	0.044917	0.663792	199223.3	282660	0.265152
0.410256	0.379114	0.401515	0.020605	0.929838	191678.9	25805759	0.401515
0.615385	0.052	0.257576	0.045172	0.673077	199200.1	2670417	0.257576
0.181818	0.395722	0.436364	0.003897	0.924062	181450.6	26170635	0.436364
0.606061	0.015725	0.145455	0.059289	0.613685	199187.3	2703769	0.145455
0.358974	0.381024	0.363636	0.02337	0.932938	183771.9	26397627	0.363636
0.653846	0.016067	0.212121	0.050612	0.6016	199466	2694433	0.212121
0.181818	0.395722	0.436364	0.003897	0.924062	181450.6	26170635	0.436364
0.606061	0.015725	0.145455	0.059289	0.613685	199187.3	2703769	0.145455
0.358974	0.381024	0.363636	0.02337	0.932938	183771.9	26397627	0.363636
0.653846	0.016067	0.212121	0.050612	0.6016	199466	2694433	0.212121
0.230769	0.387644	0.613636	0.022219	0.901069	172398.2	24625171	0.613636
0.602564	0.038951	0.174242	0.053108	0.618615	199723.1	2723558	0.174242
0.384615	0.387834	0.530303	0.01877	0.933606	179593.4	26518974	0.530303
0.679487	0.016142	0.280303	0.046343	0.606932	198733	2673151	0.280303
0.320513	0.387132	0.606061	0.019347	0.922669	156821.6	25871110	0.606061
0.602564	0.016455	0.371212	0.052065	0.610992	198149.3	2535767	0.371212
0.692308	0.016363	0.265152	0.047227	0.608908	198710.2	2645250	0.265152

6.1.1.1 CO_2 emissions Correlation results

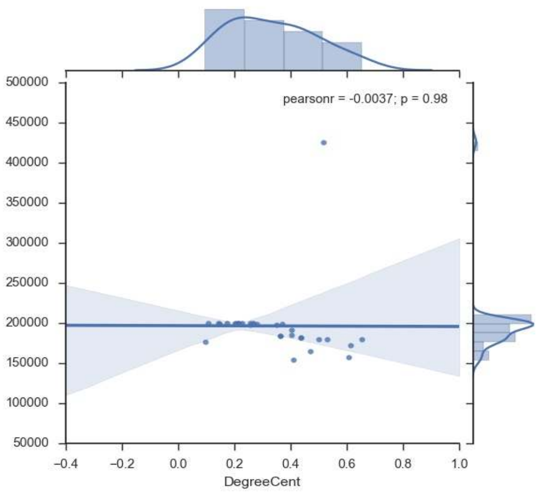


Figure 19: Correlation Degree Centralization vs CO_2 emission

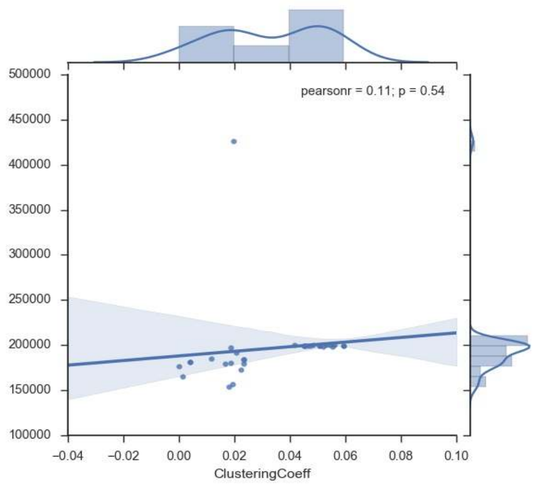


Figure 20: Correlation Cluster coefficient vs CO_2 emission

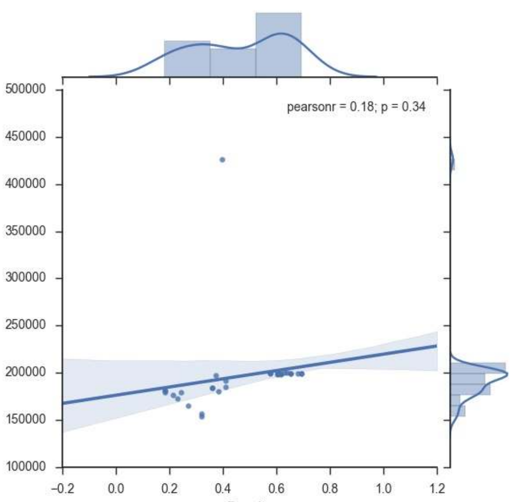


Figure 21: Correlation Density vs CO_2 emission

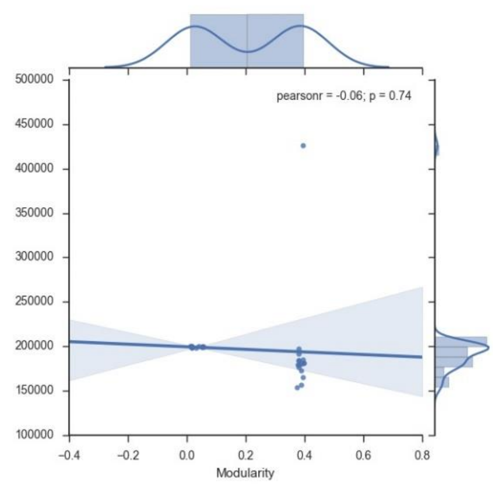


Figure 22: Correlation Modularity coefficient vs CO_2 emission

Figures 19 through 22 display the correlation relation results bestween *degree centralization*, *cluster coefficient*, *density*, *modularity* and CO2 *emissions*, respectively. As it can be seen, the Pearson coefficients are very low, with p-values all greater than 0.05. This is an indication that there are no correlations between those factors. The level of emissions does not seem to be contingent upon changes in the independant variables, taken individually. We then perform a multiple regression, in order to determinee what other factors may have a more significant influence on CO_2 emissions.

Table 12: OLS Regression Results - CO2 emissions - 1

OLS Regression Results						
Dep. Variable:	CO2Emission		R-squared:		0.008	
Model:	OLS		Adj. R-squared:		-0.061	
Method:	Least Squares		F-statistic:		0.113	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	1.94E+05	2.00E+04	9.691	0	1.53E+05	2.35E+05
DegreeCent	2.75E+04	7.96E+04	0.345	0.732	-1.35E+05	1.90E+05
Modularity	-3.23E+04	6.81E+04	-0.475	0.638	-1.72E+05	1.07E+05

Table 13: OLS Regression Results - CO2 emissions - 2

OLS Regression Results						
Dep. Variable:	CO2Emission		R-squared:		0.108	
Model:	OLS		Adj. R-squared:		0.013	
Method:	Least Squares		F-statistic:		1.135	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	5.77E+04	7.89E+04	0.731	0.471	-1.04E+05	2.19E+05
DegreeCent	2.68E+04	7.68E+04	0.348	0.73	-1.31E+05	1.84E+05
Modularity	2.10E+05	1.18E+05	1.779	0.086	-3.18E+04	4.51E+05
Density	2.10E+05	1.18E+05	1.779	0.086	-3.18E+04	4.51E+05

Table 14: OLS Regression Results - CO2 emissions - 3

OLS Regression Results						
Dep. Variable:	CO2Emission		R-squared:		0.115	
Model:	OLS		Adj. R-squared:		-0.016	
Method:	Least Squares		F-statistic:		0.8746	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	3.68E+04	9.32E+04	0.395	0.696	-1.55E+05	2.28E+05
DegreeCent	1.58E+04	8.19E+04	0.193	0.848	-1.52E+05	1.84E+05
Modularity	2.11E+05	1.77E+05	1.191	0.244	-1.52E+05	5.74E+05
Density	1.97E+05	1.23E+05	1.596	0.122	-5.62E+04	4.49E+05
ClusteringCoeff	5.88E+05	1.35E+06	0.436	0.666	-2.18E+06	3.35E+06

Tables 12, 13, and 14 display the coefficients of the multiple regression equation with *DegreeCent* and *Modularity* as independent variables; *DegreeCent*, *Modularity,* and *Density,* as independent variables*;* and *DegreeCent*, *Modularity, Density* and *ClusteringCoeff* as independent variables, respectively. The reason we performed these tests is to evaluate the effects of these independent variables as a combination on the variations of the dependent variable, here CO_2 *emissions*. These effects are measured by the value of *R-squared*, which represents the explained variation; that is, the proportion of variation which is due to the independent variables in the data set. According to the Table 12, 0.8% of variation is explained; for Table 13, 10.8% and Table 14, 11.5%. We can also deduce the effects of each of the independent variable, with *Modularity* accounting for only 0.8% - Table 12, *Density* accounting for only 10% - Table 13 (0.108 – 0.008), and *ClusteringCoeff* accounting for only 0.7% - Table 14 (0.115 – 0.108), with no statistical significance for any of these variables.

6.1.1.2 Reliability Correlation results

Figures 23 through 26 display the correlation relation results bestween *degree centralization*, *cluster coefficient*, *density*, *modularity* and *reliability*, respectively. As it can be seen, the Pearson coefficients are very high, with p-values all lesser than 0.05. This is an indication that there are correlations between those factors. The level of reliability of the grids seem to be contingent to changes in the independant variables, taken individually. We perform a stepwise regression, in order to determinee whether the combination of factors may have a more significant influence on *reliability*.

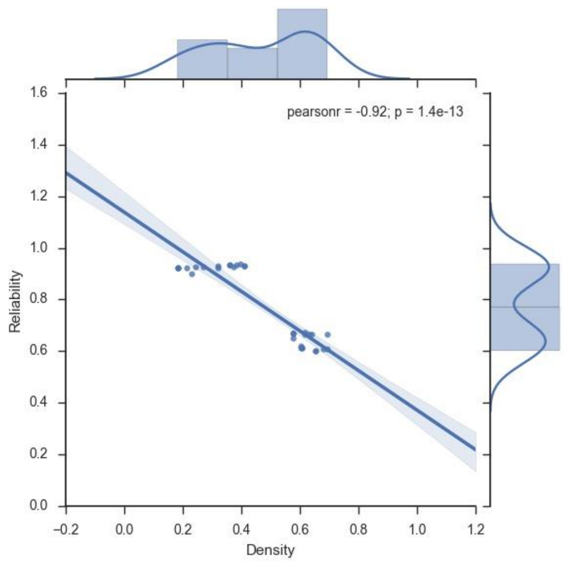


Figure 23: Correlation Density vs Reliability

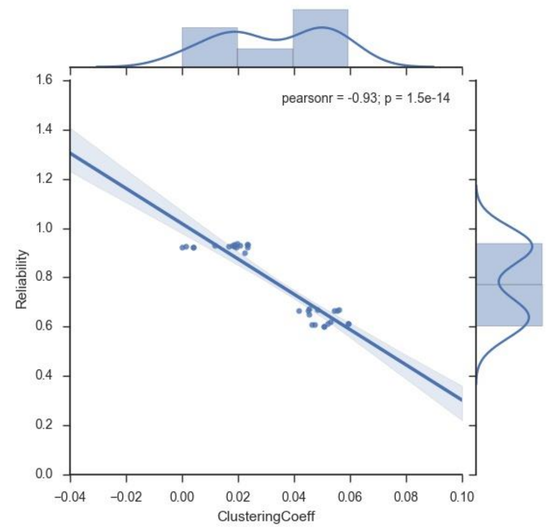


Figure 24: Correlation Cluster coefficient vs Reliability

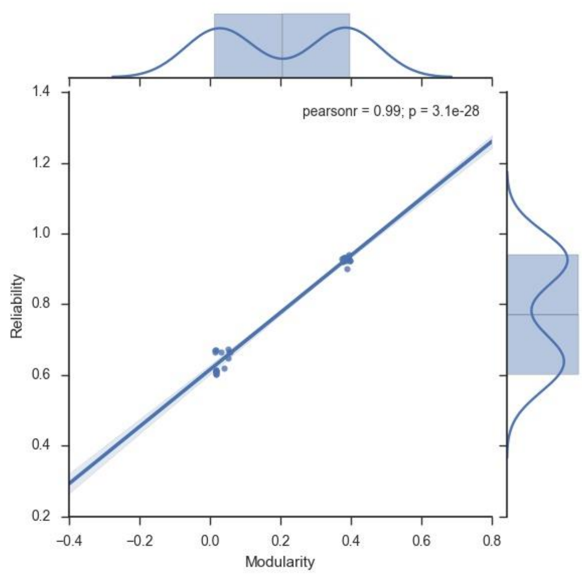


Figure 25: Correlation Modularity vs Reliability

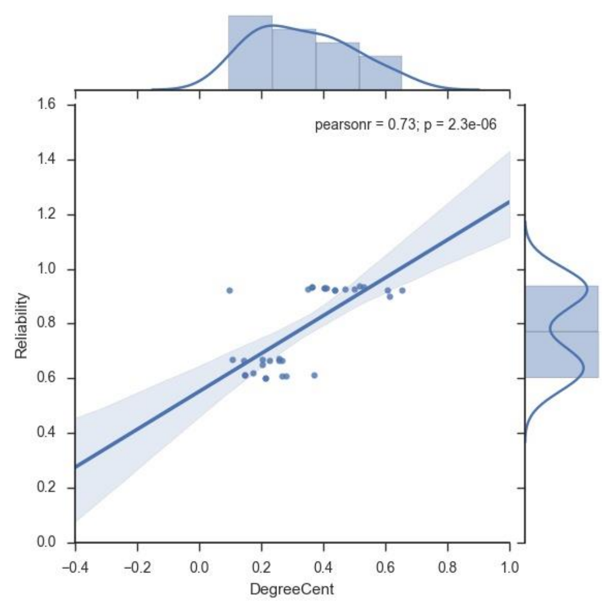


Figure 26: Correlation Degree Centralization vs Reliabilility

Table 15: OLS Regression Results - Reliability - 1

OLS Regression Results						
Dep. Variable:	Reliability		R-squared:		0.983	
Model:	OLS		Adj. R-squared:		0.983	
Method:	Least Squares		F-statistic:		1770	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	0.6151	0.005	117.261	0	0.604	0.626
Modularity	0.8072	0.019	42.073	0	0.768	0.846

Table 16: OLS Regression Results - Reliability - 2

OLS Regression Results						
Dep. Variable:	Reliability		R-squared:		0.983	
Model:	OLS		Adj. R-squared:		0.983	
Method:	Least Squares		F-statistic:		1770	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	0.6151	0.005	117.261	0	0.604	0.626
Modularity	0.8474	0.058	14.553	0	0.728	0.967
ClusteringCoeff	0.4046	0.552	0.733	0.469	-0.724	1.534

Table 17: OLS Regression Results - Reliability - 3

OLS Regression Results						
Dep. Variable:	Reliability		R-squared:		0.984	
Model:	OLS		Adj. R-squared:		0.982	
Method:	Least Squares		F-statistic:		561.2	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	0.5951	0.042	14.184	0	0.509	0.681
Modularity	0.8453	0.07	12.144	0	0.703	0.988
ClusteringCoeff	0.4125	0.577	0.714	0.481	-0.77	1.595
Density	-0.0032	0.055	-0.059	0.954	-0.116	0.11

Similarly to the previous section, these tables provide the coefficients of the stepwise regression equations. Table 15 presents the first step, with only *modularity* as independent variable*, R-squared* value of 0.984 and p-value lesser than 0.05. Table 16 presents the second step, with *Modularity* and *ClusteringCoeff* as independent variables. Both *R-squared* and *Adjusted R-square* values are unchanged, which indicates that the addition of the variable

ClusteringCoeff did not improve the model, or ameliorate the explained variation. In addition, the p-value is greater than 0.05, which means that any relationship between *reliability* and *ClusteringCoeff* are most likely due to chance. The same observation can be made in Table 17, with variables *ClusteringCoeff* and *Density* added, without improvement (*Adjusted R-square* is decreased). Based on these results, only the variable *Modularity* seems to be the only influencer of grid reliability. The other independent variables are more likely correlated to *modularity*, which explain their high correlation with *reliability*.

6.1.1.3 Financial performance Correlation results

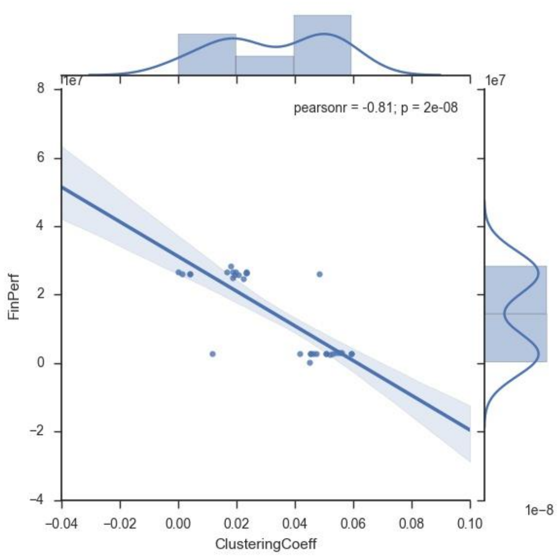


Figure 27: Correlation Cluster coefficient vs Finances

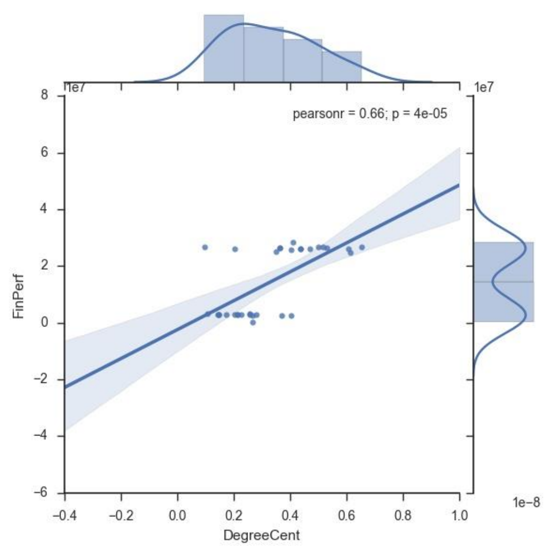


Figure 28: Correlation Degree Centralization vs Finances

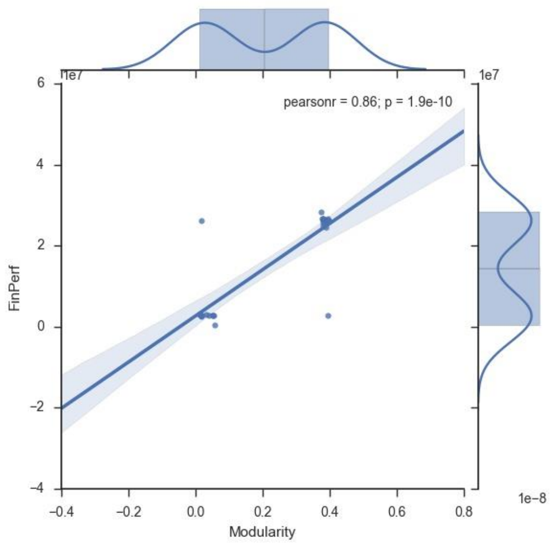


Figure 29: Correlation Modularity coefficient vs Finances

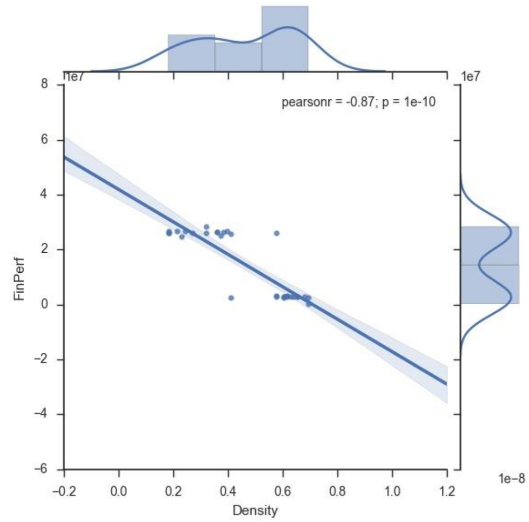


Figure 30: Correlation Density vs Finances

Figures 27 through 30 show the correlation coefficients between *financial performance* and *clustering coefficient*, *degree centralization*, *modularity*, and *density*, respectively. We notice high correlation coefficients, with p-values lesser than 0.05. We perform a stepwise regression to evaluate the independent variable with the most influence on *financial performance*.

Table 18: OLS Regression Results - Fin. Performance - 1

OLS Regression Results						
Dep. Variable:	Fin. Performance		R-squared:		0.757	
Model:	OLS		Adj. R-squared:		0.749	
Method:	Least Squares		F-statistic:		93.46	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	4.19E+07	3.03E+06	13.808	0	3.57E+07	4.81E+07
Density	-5.91E+07	6.11E+06	-9.667	0	-7.16E+07	-4.66E+07

Table 19: OLS Regression Results - Fin. Performance - 2

OLS Regression Results						
Dep. Variable:	Fin. Performance		R-squared:		0.781	
Model:	OLS		Adj. R-squared:		0.766	
Method:	Least Squares		F-statistic:		51.65	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	2.43E+07	1.03E+07	2.349	0.026	3.14E+06	4.54E+07
Density	-3.33E+07	1.57E+07	-2.119	0.043	-6.54E+07	-1.15E+06
Modularity	2.71E+07	1.53E+07	1.774	0.086	-4.14E+06	5.84E+07

Table 20: OLS Regression Results - Fin. Performance - 3

OLS Regression Results						
Dep. Variable:	Fin. Performance		R-squared:		0.784	
Model:	OLS		Adj. R-squared:		0.761	
Method:	Least Squares		F-statistic:		33.97	
	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
const	1.97E+07	1.24E+07	1.593	0.122	-5.63E+06	4.50E+07
Density	-3.59E+07	1.63E+07	-2.202	0.036	-6.93E+07	-2.50E+06
Modularity	3.64E+07	2.05E+07	1.776	0.087	-5.59E+06	7.85E+07
ClusteringCoeff	1.17E+08	1.70E+08	0.689	0.497	-2.31E+08	4.66E+08

Tables 18, 19, and 20 show the results of the stepwise regression analysis performed. We notice that the value of *Adjusted R-square* decreases in the last table, despite a slight increase in the value of *R-square*. The addition of the variable *Modularity* in Table 19 improves the model but is not statistically significant. It may thus be due to chance. The rise of the explained variation might thus just be due to chance. The variable *density* is the only statistically significant predictor.

6.1.1.4 Additional statistical tests

The results obtained in the previous section indicate that there might be a correlation between all independent variables. These variables are strongly associated with dependent variables individually yet do not improve the model when combined together. We will thus run a

Principal Components Analysis (PCA). One of the main qualities of this widely used multivariate statistical method is variable dimension reduction (Abdi and Williams 2010), allowing the transformation of multiple variables into fewer main components. This transformation leads to important information being extracted from a bigger proportion of multi-dimension data composed of variables correlated with one another. This extraction is done via a reduced number of components, called *Principal Components* (PC), showing no correlation between them and ranked so that the first components explain most of the variation in the original data (Jolliffe 2002).

The number of principal components is revealing of the amount of variance in the data which can be explained by these components. The importance in the decision of this number is explained in various studies, namely Hayton et al. (2004), or Fabrigar et al. (1999), among others. Being able to filter and distinguish important components from trivial ones helps expressing in a more appropriate manner the existing correlations between elements. By picking them out, the extraction of the most important information from the data takes place, leaving the rest of the information as the result of chance or randomness. Defining the right number potentially guards against both *underextraction* (retaining less components than required) and *overextraction* (retaining more components than required) (Ledesma and Valero-Mora 2007). These situations, according to Zwick and Velicer (1986) are responsible for the loss of relevant information, leading to significant error in the solution with strong variables loading on potentially several components and leading to less grave error with factors with few substantial loading, respectively, which jeopardizes the interpretation of the results.

We need first to perform the KMO (Kaiser-Meyer-Olkin) and Bartlett's test of sphericity to assess the relevance of performing PCA. The KMO test answers the question to know the appropriateness of the PCA test in the first place, in terms of knowing whether the information looked for can be obtained from the PCA technique. The Bartlett's test of sphericity tests whether or not the correlation matrix is an identity matrix. An identity matrix indicates that there is no correlation between the variables, making data reduction almost impossible. Obtaining such matrix would indicate that the model is inappropriate. The test also tests the null hypothesis that the variables in the correlation matrix are uncorrelated (Krishnan 2010).

Table 21: KMO & Barlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.792
Bartlett's Test of Sphericity	Approx. Chi-Square	148.698
	df	6
	Sig.	0.00

Table 21 shows a significance level of 0.00, which is low enough, if we consider a 95% level of confidence, to deduce that the correlation matrix is not an identity matrix. The relationship or correlation among variables is therefore strong enough. In addition, the KMO index, which ranges from 0 to 1, is considered suitable for PCA in our case, given that the value presented in the table is greater than 0.50 (Constantin 2014).

Table 22: Component extraction

Total Variance Explained						
Components	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Density	3.449	86.225	86.225	3.449	86.225	86.225
Modularity	0.412	10.297	96.521			
DegreeCent	0.098	2.441	98.962			
ClusteringCoeff	0.042	1.038	100			

According to Table 22, only the variable *density* is extracted, meaning that this is the main predictor and driver of variation in the data, with 86.2255% of explained variance. This result confirms the suspicions noted earlier in the previous section. Table 23 displays the correlation coefficients between all the independent variables.

Table 23: Correlation matrix

		Density	Modularity	DegreeCent	ClusteringCoeff
Correlation	Density	1	-0.927	-0.698	0.903
	Modularity	-0.927	1	0.755	-0.943
	DegreeCent	-0.698	0.755	1	-0.647
	ClusteringCoeff	0.903	-0.943	-0.647	1

In Table 24, we show, based on the test results obtained, the relationships between grid network structure or architecture features and grid performances. As the density level goes up, the grid level of reliability drops and decreases in performance in terms of finances (costs are going up). The impact of the other independent variables can be deduced from Table 23 given their correlation with the variable *density*. The more clustered the grid is, the less reliable and more costly the grid becomes. Unlike those two variables, changes in the levels of *Modularity* and *DegreeCent* cause the grid to perform differently. The more modular the grid gets, the more reliable and less costly the grid evolves to be. Similar observation for the level of centralization.

As the grid gets more centralized, the level of reliability and financial performances improve. Given the results we had, the level of emissions is not dependent on the architecture of the grid.

Table 24: Relationship grid structure and grid performance

	Fin. Performance	Reliability	CO2 Emissions
Density	-	-	*
Modularity	+	+	*
DegreeCent	+	+	*
ClusteringCoeff	-	-	*

Practically, a dense network is a network in which the number of links of each node is near the maximum number of nodes. That is, each node is linked to almost all other nodes. By contrast, a sparse or less dense network would be connected with a low number of links. In our case (power grid network), the level of density in the grid refers to how connected the grid is through transmission lines.

6.1.2. Case 1 Illustration

We look at the differences in performance between two generated grids. We record the features of their architectures and analyze their associated performances. Let's call these grids GridX and GridY. Table 25 shows how both grids came about.

Table 25: Actions taken to generate gridX and gridY

Year	Actions	
	gridX	gridY
2010	Initial grid	
2014	Add generation capacity in all zones in deficit.	Add transmission capacity, aiming to all zones in excess, and which did not import power, to zones in deficit
2018	Add generation capacity in all zones in deficit.	Add transmission capacity, aiming to all zones in excess, and which did not import power, to zones in deficit
2022	Add transmission capacity, aiming to all zones in excess, and which did not import power, to zones in deficit	Add generation capacity in all zones in deficit.
2026	Add generation capacity in all zones in deficit.	Add transmission capacity, aiming to all zones in excess, and which did not import power, to zones in deficit
2030	Add generation capacity in all zones in deficit.	Add transmission capacity, aiming to all zones in excess, and which did not import power, to zones in deficit

Table 26: Architectural characteristics of gridX and gridY

	gridX	gridY
Density	0.269231	0.679487
Modularity	0.392935	0.016142
DegreeCent	0.469697	0.280303
ClusteringCoeff	0.001286	0.046343

Table 26 displays the architectural features of the grids (GridX and GridY). As it can be seen, gridY is denser with a higher level of clustering. Communities are larger with multiple countries/zones exchanging power between them. These are [Ghana, Burkina Faso, Cote d'Ivoire, Sierra Leone], [Liberia, Togo/Benin, Gambia, Niger, Nigeria], [Senegal, Mali], and [Guinee-Bissau, Guinea]. The larger the communities, the lower the modularity, as the network is more integrated. GridX presents a different structure with communities that are smaller, including [Ghana, Cote d'Ivoire, Burkina-Faso], and [Nigeria, Togo/Benin, Niger]. GridX is a more fractured network, with Nigeria, Ghana and Cote d'Ivoire being the main suppliers of power throughout the network.

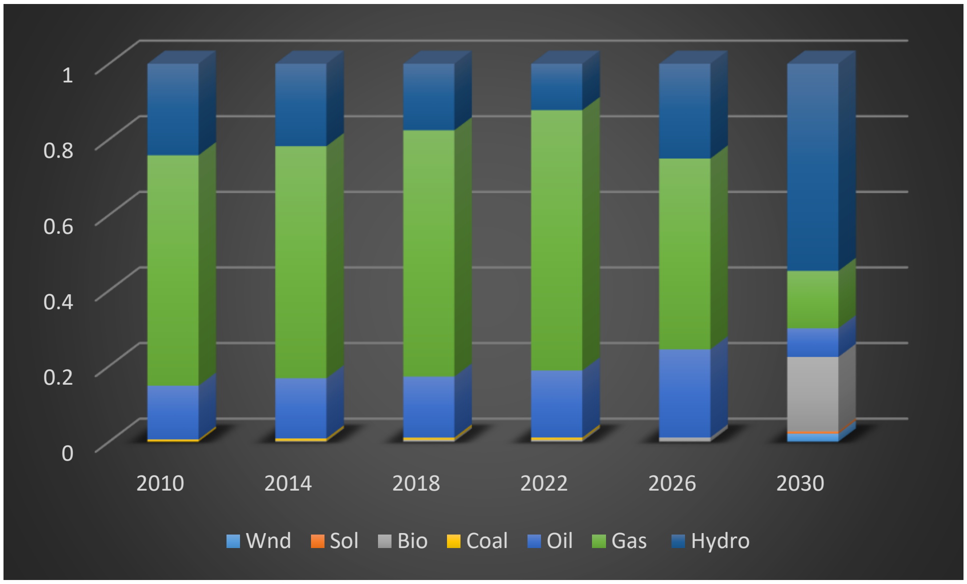


Figure 31: Generation mix. GridX. Year 2010 to 2030.

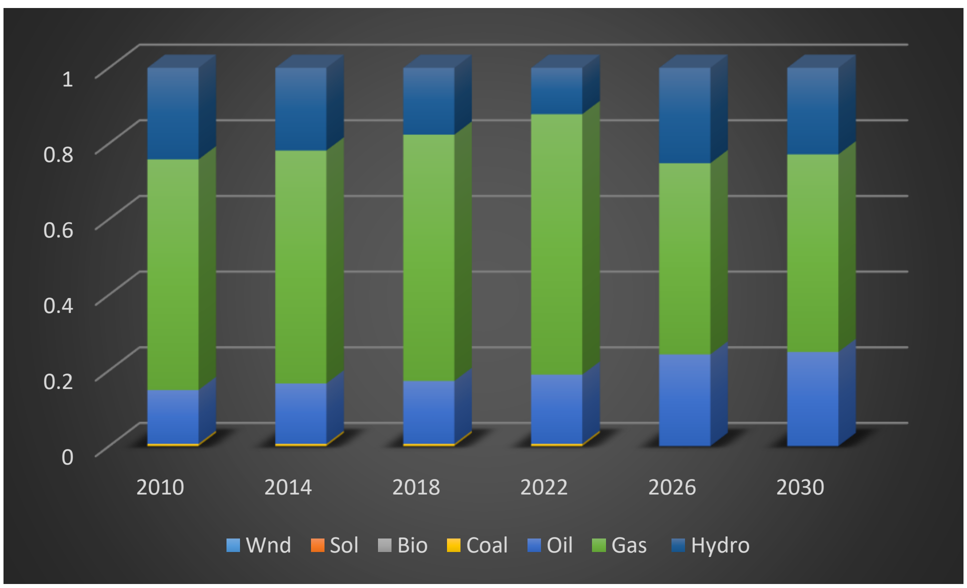


Figure 32: Generation mix. GridY. Year 2010 to 2030

Compared to GridX, GridY is obtained with more emphasis on transmission capacity addition. Figure 32 displays the generation mix of GridY, which indicates limited use of renewable sources, with an increase use of oil over time. Because virtually no investment is in capacity generation, demands are met with only existing plant technology, which in this case are mainly fossil fuel. In Figure 31 we notice the presence of more renewable sources being used, due to investments in renewables, in replacement of fossil fuel power plants. Figure 33 expectedly shows a drop in reliability level for GridY since no generation is added, while demand is increasing. The level of reliability is seen to increase in GridX as local fleet generation is adjusted to demand needs.

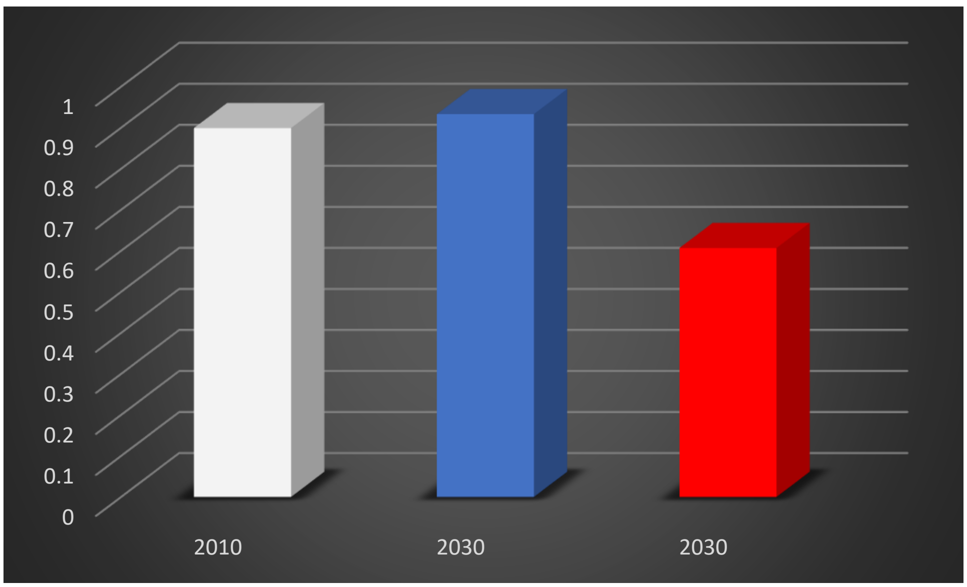


Figure 33: Grid reliability, for the whole network, 2010 and 2030. Blue for GridX, Red for GridY

Figures 34 and 35 display the financial performances of the grids, indicating more profits for gridX than gridY. These costs reflect the plants usage rate and ultimately the energy mix. The higher the proportion of conventional source is in the energy mix, the higher the fuel costs, and consequently, the lower the economic gains in the network.

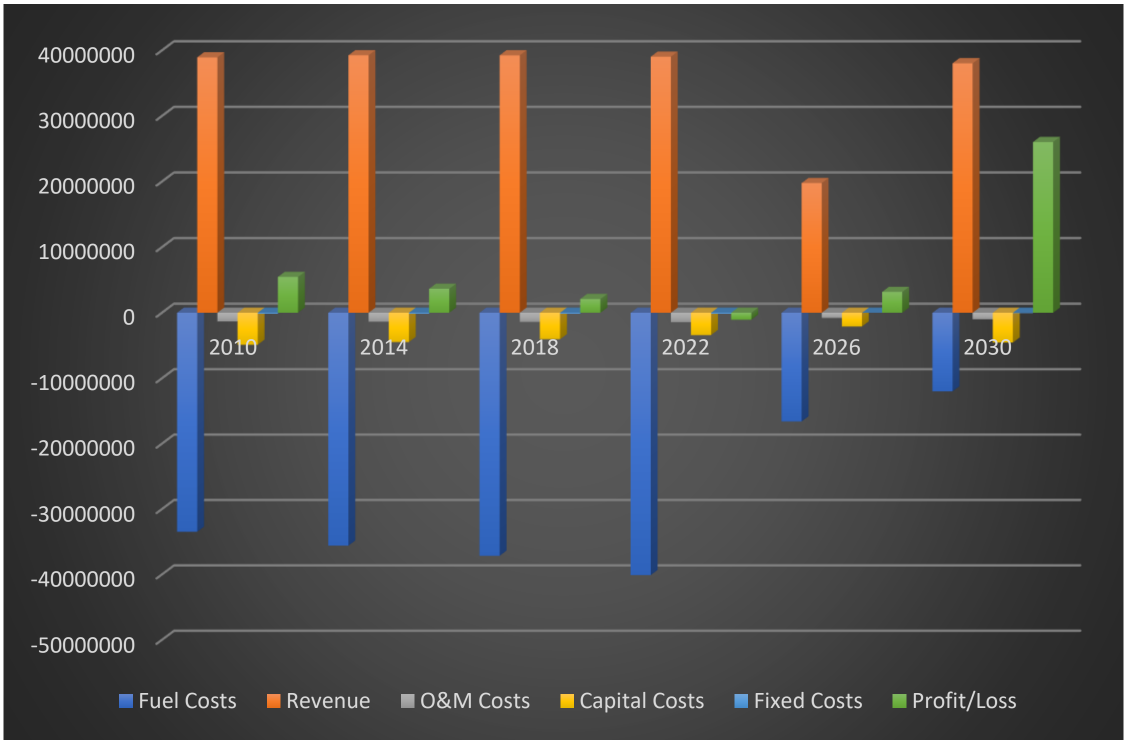


Figure 34: gridX financial performance from 2010 to 2030.

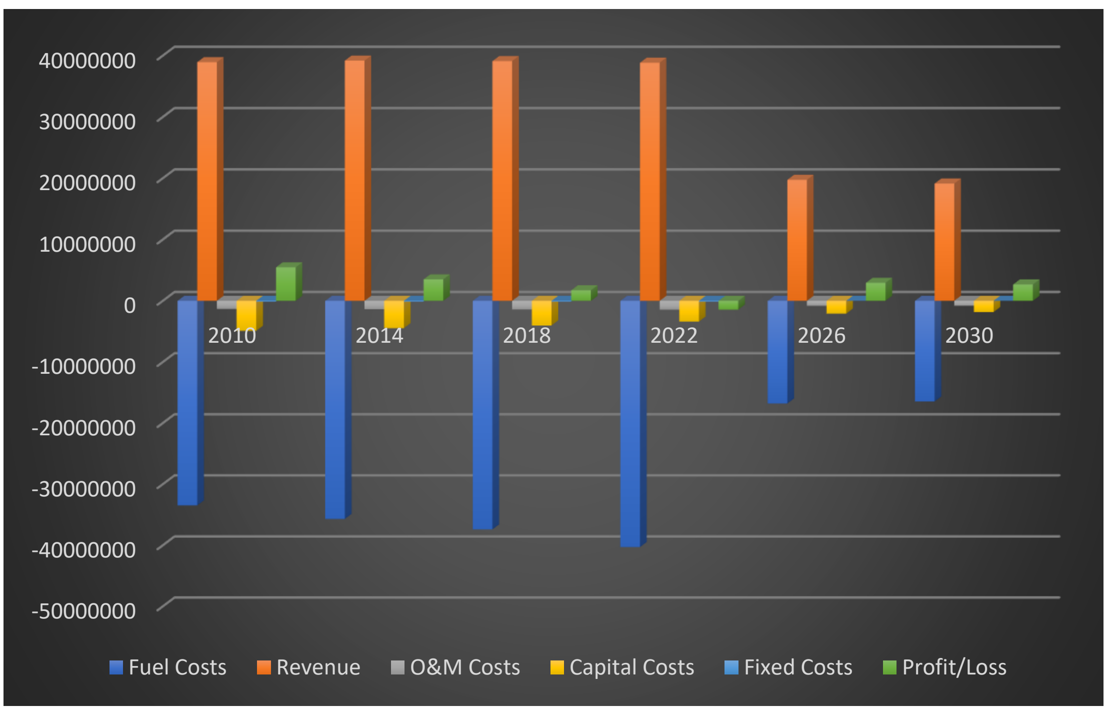


Figure 35: gridY financial performance from 2010 to 2030

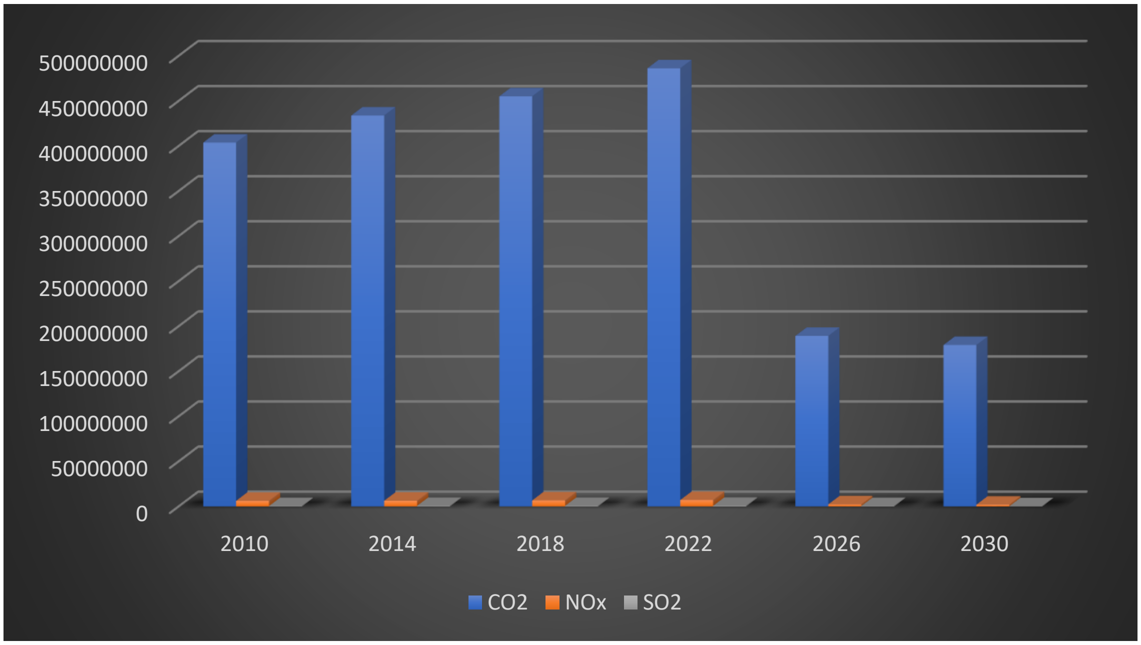


Figure 36: gridX gas emissions from 2010 to 2030

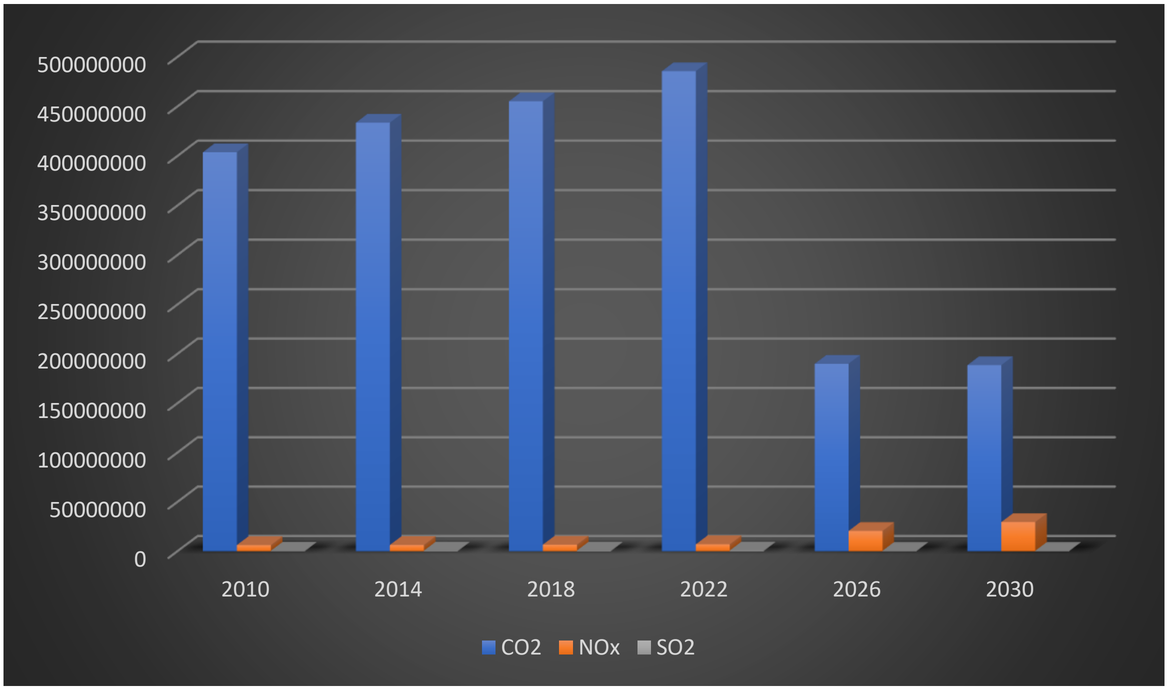


Figure 37: gridY gas emissions from 2010 to 2030

In Figures 36 and 37, we observe the emissions of GridX and GridY, respectively, with a seemingly similar pattern through the scenario run. The period of 2010 to 2022 is marked by an increase in gas and oil usage to cope with the increase in demands. These emissions are reflected in the costs, with heavy fuel costs limiting the profits. Because of the lack of renewable plants, gas plants are the most used, given their heavy presence in the grid network. Year 2022 coincides with most of these plants being retired and in need of replacement. While renewable plants are added to the generation fleet in GridX, transmission lines are added in GridY. As a result, in both cases, emission levels drop since in GridX, renewables do not emit, and in GridY, conventional plants are not replaced. The drop in reliability in Figure 33 is a result of this non-replacement. Increasing demands are not being met.

In GridX, decisions enabled plants to be built anytime deficit was noticed across the grid network without too much regard for transmission. As a result, transition toward renewables could more easily happen. The integration rate of renewables was dependent on the occurrence of deficits, as anytime there is deficit, there is addition of renewable generation capacity. Not only does this grid favor renewable integration, it also provides improvement in reliability level. This is not the case for GridY, where the focus was placed on interconnection. This grid has evolved to become much more interconnected, but with insufficient generation assets. Demands in the network could only be met by existing plants. However, when those happen to retire and are not replaced, demands, which in the meantime are growing, remain unsatisfied. Such a grid not only limits renewable integration but also negatively affect electricity access.

6.1.2 Results interpretation

Under our scenario, it is clear that denser grids in West Africa would not be beneficial (Figures 34 and 35), especially if not complemented with capacity generation additions in countries in power deficit. While growth in demand is happening, the installed capacity of the electrical network infrastructure - rather than remaining static - needs to be invested in, unlike in GridY. In years, the electrical supply network has been overstretched. For example, in a country as economically powerful as Nigeria, the only plants that were last commissioned are the Egbin gas turbine plant and the Shiroro Hydro plant, in 1996 and 2004, respectively (Edomah, Foulds, et al. 2017). Despites these provisions, Nigerian demands were still greater than supply, and the country relies to import (USAID 2015).

A strong WAPP would necessarily have to involve strong local/zonal grids, which will favor the integration of renewable sources, as shown in the case of GridX. That way, the WAPP grid will gain not only in reliability, but also costs. By using its vast and largely untapped renewable energy potential, West African nations could improve electricity access rates and provide electricity for all more rapidly. Where the goal is expanding energy access, especially to rural communities, such an approach deserves priority, as it would feature lower costs and shorter wait times compared with grid extension. Without doubt, grid extension in this part of the world is also critical, as it would contribute to a more effective use of renewable resources and a more performant grid. Countries like Niger or Sierra Leone may benefit from a denser grid given their weak economy and lack of investment in the power sector. Importing from Ghana or Cote d'Ivoire, where supply is more reliable, would considerably improve their supply-demand balance.

6.2 Case 2: Grid Coordination Operation

Grid balancing is a critical system requirement in power grid architecture for matching the supply to the demand. This balancing has historically been achieved by conventional power generators. Electricity planning was considerably less complex, given fairly predictable rises in electricity demand with a shift to predominantly larger generating plants (Kagiannas, Didis et al. 2003). This is no longer the case, as renewable penetration brings more variability and uncertainty to the grid (Ela, Diakov et al. 2013, Bessa, Moreira et al. 2014), which have considerable impacts and implications on power system reliability and efficiency as well as costs. The higher the renewable penetration in the grid, the lower the ability to forecast output with accuracy. It is argued that coordinating BA operation would promote more cost and resource efficient integration of renewable energy (Milligan and Kirby 2007, Katz, Denholm et al. 2015). The integration of variable renewable energy can be eased and furthered, and savings can be achieved via sharing or coordinating resources across multiple BAs. Consolidation or coordination can occur in a multiple of ways. We propose to compare two types of coordination, which we call Aggregated Balancing Areas Operation (ABAO) and Disaggregated Balancing Areas Operation (DBAO). In comparing them, we are looking to identify strengths and weaknesses of either coordination type in terms of costs and renewable source usage.

6.2.1 Aggregated Balancing Areas Operation (ABAO)

Under ABAO, the grid is composed of a balancing authority at the network level, which performs the unit commitment task. We will call it BNA (Balancing Network Authority), which, like a vertically integrated entity, has direct control and access to all power supply units in the whole grid. This consolidation co-optimizes the generation fleet for maximum economic benefit and least-cost renewable integration while considering transmission adequacy. The unit dispatch is carried out by several balancing authorities at the area level which belong each to a balancing area. We will call them Balancing Area Dispatcher (BAD). This balancing ensures, based on generation/consumption exchange information, that demand and supply are matched at all times. If not, BADs take appropriate actions, including managing trading of electricity with other balancing authorities. This trading is a bid-based bilateral exchange market (Dempsey 2011), where bids to buy and/or offers to sell electricity are shared between BAs in a horizontally integrated structure. Depending on their needs, buying and selling areas agree to a transaction, which is handled bilaterally. This allows the selling BAs to export excess power to the highest bidding BA and maximize profit. Once agreements are met, power is physically exchanged between balancing areas. Figure 38 illustrates these coordination mechanisms.

6.2.2 Disaggregated Balancing Areas Operation (DBAO)

Under DBAO, the grid does not have a balancing authority at the network level unlike in the ABAO case. The unit commitment task is performed at the area level, by an entity we will call BAC (Balancing Area Committer), which belongs each to a balancing area. BAC has direct control and access to all power supply units only in the corresponding area. This arrangement also co-optimizes the generation fleet for maximum economic benefit and least-cost renewable integration but without transmission requirements since only units are committed to match local demand. This is the key difference, compared to ABAO. The unit dispatch is carried out in the same manner. Figure 39 illustrates these coordination mechanisms.

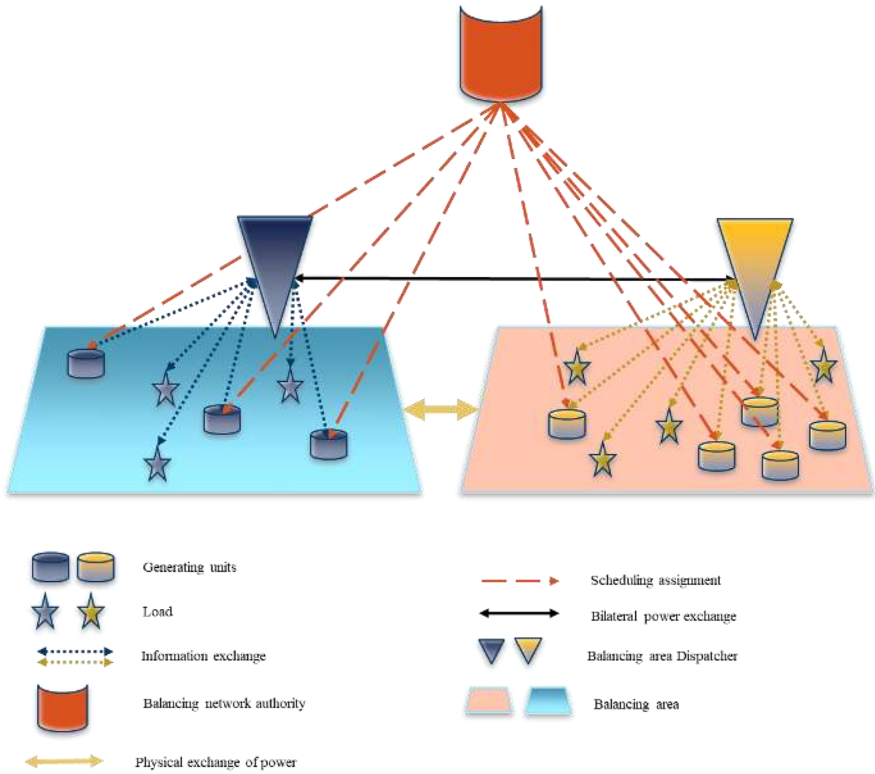


Figure 38: Illustration of ABAO power grid coordination mechanisms

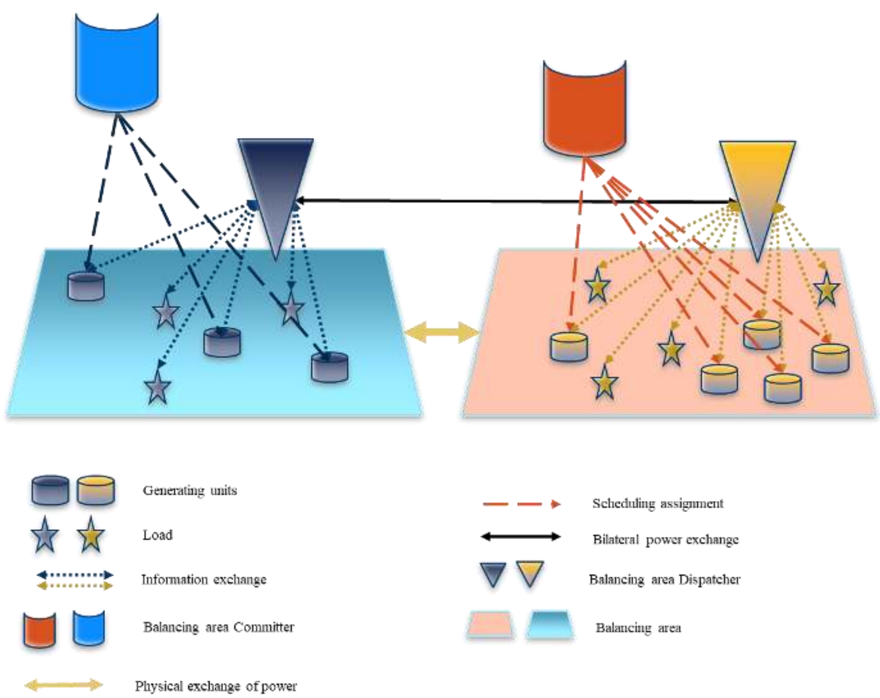
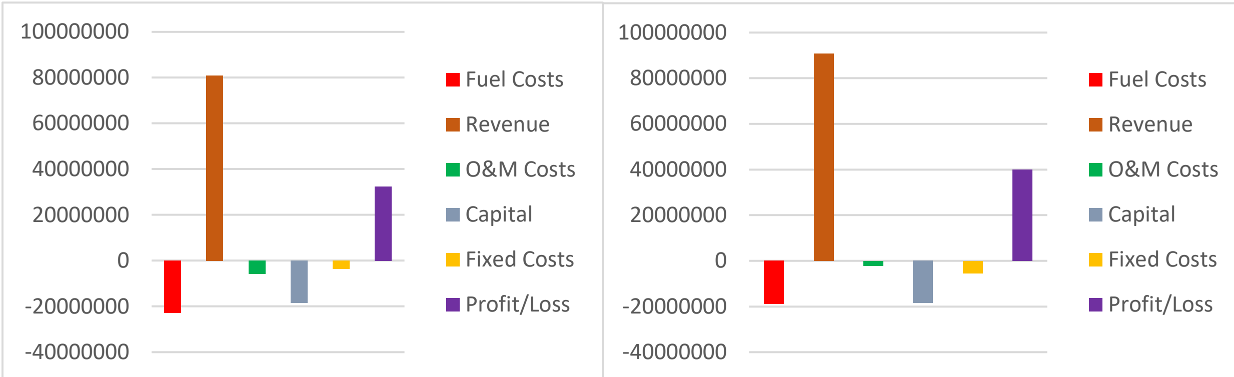


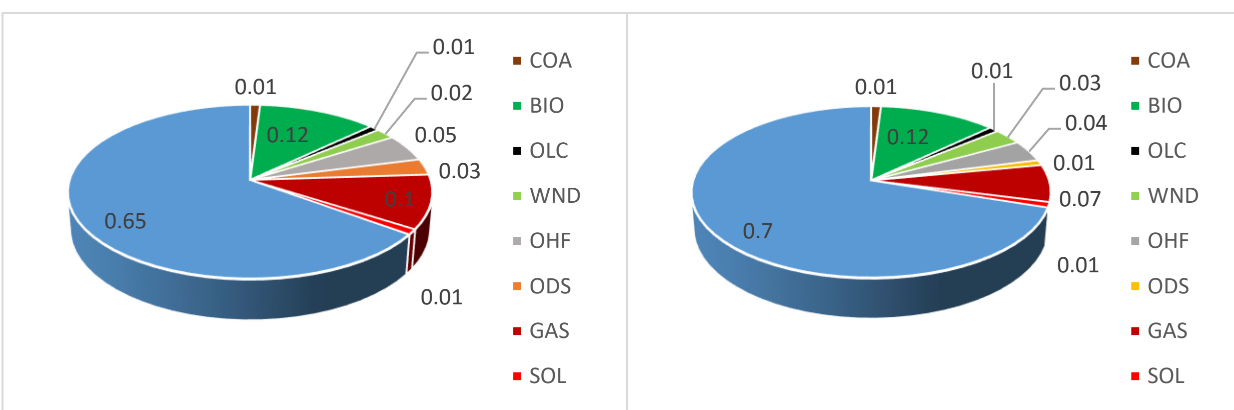
Figure 39: Illustration of DBAO power grid coordination mechanisms



(a) Financial performance DBAO (b) Financial performance ABAO

Figure 40: Financial performance, in RPS, measured by Profit/Loss, taking into account fuel costs, revenues, capital costs, fixed costs and O&M (operation and maintenance) costs: (a) DBAO coordination type, (b) ABAO coordination type.

The financial performance looks at the total costs of unit commitment and deployment over the simulation run. How much profit/loss is made in ABAO and DBAO, comparing the revenues and all incurred costs? Figure 40 shows a higher economic gain in ABAO, with less fuel costs and more revenues. This is expected, considering that this coordination type favors more the deployment of renewable. This is confirmed in figure 39, displaying the energy mix for both coordination types.



(a) Energy Mix – DBAO (b) Generation Mix - ABAO

Figure 41: Energy mix for the WAPP grid: (a) DBAO, (b) ABAO.

Figure 41 shows more HYDRO power used, with slightly more WIND in ABAO compared to DBAO. ABAO makes a better use of renewable, with less fuel sources deployed.

The two types of coordination operation offer different results in terms of power generation and financial performances. The consolidated scheduling in ABAO helps establish a complete system of governance over generators and transmissions systems. The BNA, because of its access to all generators in the whole grid, can set up a schedule and sequence of units, accounting for costs minimization and transmission constraints at the network level. As seen in the previous results, there is a more important proportion of renewable in the energy mix. This also translates at the economic level, with lower fuel costs and slightly lower O&M costs. Renewable sources do not incur any fuel costs, and carry minimal maintenance costs. DBAO, as explained earlier, functions differently with costs minimization limited to the BA level. It thus limits the ability of different BAs to cooperate and coordinate resources. As a consequence, local generators, across the grid network may be unnecessarily used. BACs are primarily concerned with meeting local demands, only scheduling local generation fleet. In that sense, if mostly conventional sources are available, they would most likely be deployed. The same thing can be said if most sources are renewable. However, what makes the difference is the amount of resource sharing across the grid. Our results show heavier usage of conventional sources in DBAO, with lower profits. ABAO performs better than DBAO, financially, given its ability to minimize costs globally, rather than locally.

6.2.3 Results interpretation

According to the results obtained, DBAO would not be as profitable for grids in West Africa (Figure 40). A strong WAPP would emerge if management policies put in place favor resource sharing, at the network level. With ABAO, the WAPP grid will present a more pronounced financial gain, with less fuel costs and O&M costs, which will considerably help boost economy in West Africa (Wesseh and Lin 2016). It offers a more efficient sharing of renewable throughout the grid (Figure 41). Renewable sources can be transmitted to other BAs if transmission capacity allows. Where the goal is expanding energy access, especially to rural communities, such an approach, based on the results obtained, deserves priority, as it would feature lower costs.

CONCLUSION

The purpose of this research is to explore how power grid network architecture characteristics impact economic, environmental, and reliability performances of the grid. Power grids are modeled as a way to understand their behavior and perform experiments during analysis. Modeling has been, for so long, the privileged tool to answer energy planning questions, which has solidified the trust of decision makers in models results. In addition to modeling, we resort to network science in order to capture the topology of networks. This approach has also been used in the past to analyze various topological features of networks, and was therefore appropriate, especially for the increasingly complex and interconnected nature of the power grid.

Using an extensible and reusable platform, we developed a model, detailed enough to capture architectural features of the grid and technical constraints of the systems components yet abstract enough to enable a reasonably fast execution. Its main goal is to perform energy planning, by analyzing expansion plans on a long term while also performing day-to-day activities of the system. The model is technology explicit, data driven, spatially and temporally detailed, and uses stochastic algorithm. These requirements are key to simulate the time dependent behavior of large-scale power systems, considering the combined effects of the intermittence and stochastic nature of renewable energy resources and their forecast ability, the thermal constraints of conventional generation resources, geographical information, and transmission network. Using network theory, the metrics used to characterize the grid architectures are density, modularity, degree centralization, and clustering. It is our opinion that these measures describe the grid structure in a way that fits the purpose of the study.

To study the eventual influence of grid network architecture types on grid economic, environmental, and reliability performances, we selected the WAPP grid as a case study. This is a large-scale power grid with a wide variety of supply resources and a good potential in renewables. We conduct two studies: one analyzing grid evolution and performance and the other analyzing grid coordination operation types.

In the first study, we perform a statistical analysis, more specifically, a correlation analysis. The dependent variables are reliability, gas emissions, and financial profits, and the independent variable are the network metrics *density*, *modularity*, *degree centralization,* and *clustering*. As a method to collect data - that is, grids with different architectural metrics - we proposed a grid generative method. This method captures path dependency, involves both rational and subjective judgment, and helps iteratively generate grids of various architectures. The intent is to create possible grids of the future as a result of not only a continuation of repercussions of past decisions made, but also of present human choices and actions. According to the PCA test conducted, *density* is the main predictor and driver of variation in the data, explaining little over 86% of variation in grids performances. The other metrics were therefore overlooked. We found that the denser the grid, the less reliable and less economically profitable the grids tend to be. However, no association was found regarding gas emissions, which is reasonable, as emissions have more to do with energy mix than grid architecture, if anything.

In the second study, we compare two grid coordination operation types, namely ABAO and DBAO. The consolidated scheduling in ABAO helps establish a complete system of governance over generators and transmissions systems at the network level, while in DBAO, scheduling is rather localized. The objective is to assess a more advantageous grid management arrangement for the WAPP grid. Results indicate ABAO offers higher level of resource sharing, which is invaluable opportunity for renewable penetration. Cost wise, this coordination is also more profitable for this grid.

Overall, policies for accelerated deployment of renewable energy are needed, not only to reduce costs, but also emissions. However, a careful selection of strategies that are appropriate to West Africa is also primordial as they are not equally sustainable. The rationale and motivation behind the creation of power pools were to promote regional electricity integration and cooperation through grid interconnections and power pooling (AfDB, 2017), as it was deemed a cost-effective means to ensure supply-demand balance and an effective strategy to deal with Africa's energy problems (WEC, 2005). Our results suggest though that in the long term, reliable and cost-effective WAPP grid objectives are incompatible with transmission-focused decisions. It is therefore in the global interest to not only increase generation, but also appropriately invest in the transmission network. This is primordial for Africa and the African Development Bank to understand in order to help achieve continent-wide electricity access by 2025. By performing this study, we highlight the fact that ECOWAS would benefit from an improved transmission network if accompanied by an ambitious strategy to further the development of national/local generation fleet. Finding the right balance would be ideal though complex. This study's main contribution lies there: Provide insight regarding decision trajectory which could lead to a stronger WAPP grid.

It is important, though, to point out that the validity of our conclusion only extends to the boundaries of ECOWAS. Because the modeling platform used is data driven, it is appropriate to posit that such a conclusion would not have been reached had it been a different grid profile with different characteristics and weather. This research lays the foundation, however, of relationships between power grid architectures and performance: grid architectures influence performance. How? And to what extent? These questions can only be answered on a grid-by-grid basis.

From a modeling and simulation perspective, analyzing large-scale distributed systems like power grids led to few modeling and design choices we feel were beneficiary to our study.

For instance, we elected to simulate our model via the Python environment rather than an existing simulation package. Python is a high-level programming language, machine independent and convenient for managing complex tasks (Python, 2018). Because the model is built and run on a PythonPDEVS, all sub-models are written in the same language, resulting in completely interpreted execution and making it faster to generate simulation as it reduces the turnaround time (Van Tendeloo and Vangheluwe 2016). It offers more facility to write and debug complex code, which fits our needs as we were looking to build and simulate large-scale power grid operations for long-term planning purposes. In addition, using such a platform gives us freedom to build our model we desire without constraints of existing simulation packages. For example, in building the *unit commitment* atomic DEVS model, we were able to design optimization and heuristics algorithms subject to our own justified constraints and assumptions.

In this study, we took on the task to illustrate how systems like power grids – and, ultimately, all distributed systems (continuous or otherwise) - may be advantageously mapped into DEVS representations. While a differential equation solution would require a step-by-step generation of successive model states, the discrete event form would compute state changes only when events occur (Zeigler 1989). Discrete event representations afford thus a more efficient simulation. In DEVS modeling, we have time-advance and internal transition functions to specify the time and state of next boundary crossing. We also have an external transition function to trigger state transition when a change in input takes place. The challenge is to be able to match states to prerogatives or actions performed by components in the system. In our case, it was important to first discretize time, that is, determine the points in time (hour by hour) at which events would occur and states would transition. This choice was bound by the nature of data at our disposal, including hourly demand, hourly change in wind speed, solar irradiance, and water flow. Second, we had to identify tasks performed by each power grid components, define their relationships, the nature of information exchanged, and the times at which these tasks and exchange take place, and map all these to DEVS internal, external time advance and output functions.

One requirement we thought our model needed was to be data-driven. As such, the model is extensible and scalable. In that sense, in addition to specifying and analyzing the specific grid at hand, a whole class of similar systems (though with different scales, architectures, load profiles, generation supply and technology), given appropriate instantiation and dimensioning, could also be analyzed. Its scalability would also allow to handle extensive and large amount of data, including a wide range of electricity generation technology and requirements, thermal constraints, as well as fuel costs and gas emissions. This level of detail brings more credibility to the results as more real components characteristics are captured.

One last modeling choice made was the separation of concerns, which helped us separate the components of the model and their functionalities. Each component of the grid was modeled individually via Python scripts as shown in Figure 13 (component repository). Each script addresses a separate concern, that is, the main function of a specific grid component. For instance, the demand in the grid network is represented by the *load* atomic DEVS model, or the generation supply is modeled as the *generator* atomic DEVS model. Beyond the grid components, we also added Python scripts to perform the different activities of the simulation platform. Script *sim.py* for example, just launches the simulation and then produces output graphs. The graphs are generated after the simulation is completed, as opposed to simulation software Netlogo or Anylogic, which perform both at the same time. Scripts *DBModels.py* and *feedDB.py* perform activities related to database management. *feedDB.py* reads all data kept in the database, in CSV files. In this script, we write methods defining how to read the data, and then run the simulation. *DBModels.py* is an assemblage of classes and methods filtering, transforming and aggregating data, which are called upon by other classes. This modular programming approach allowed us to reduce the complexity of the system being designed. In this way, it was easier to locate and fix bugs that might emerge during the simulation.

Simulating distributed large-scale systems, it helped that PythonPDEVS is a distributed Parallel DEVS simulator, as it allows each atomic model to run not only concurrently, but also with the introduction of the confluent transition function, handles cases with input events received at exactly the same time as an internal transition is scheduled. The model ran faster. In addition, the modeling choices explained offer the model extensibility and reusability, which makes our modeling framework suitable for large-scale systems.

FUTURE WORK

There is still room for improvement in this study. The topic of integrated resource planning is very important, especially given the emergence of renewable sources and issues related to their integration. One aspect, which was not included in our study is the use of energy storage. Storage units are critical as they provide more flexibility and reliability to the grid given their fast response. An efficient use of storage would help better adjust power flow patterns, which would ultimately lead to cost savings. What is needed is an algorithm to specify their use throughout the day. The main question to answer is when to resort to them in order to maximize their roles in a high renewable penetration grid.

Another aspect is forced and planned outage. These operational constraints are modeled but not implemented. It would be interesting to examine the effects those factors would have on unit commitment and dispatch processes as well as the repercussions on costs and reliability.

Last, the limited choice for decision making in the heuristic method may be addressed in future studies. In this study, we only consider two options - build either generation or transmission lines - which are only based on unmatched demand and resource potential. An additional action that can be considered, for instance, is to expand an existing generation. Several factors can also be taken into account, including cost analysis to determine the location to build generation, generation type, or transmission lines to build that would be most cost effective, change in policy in regard of investment in a given resource type, and grid performance (in addition to reliability).

One critical limitation regarding the modeling architecture used is that the model is very data intensive. Given the level of details considered (operational constraints, costs, weather data, load profile, supply fleet data, etc.), it would (extremely) be time consuming to study different grids, especially if they are of large scale. Data must be entered manually in all CSV files, and in the pre-defined format. It would be interesting to investigate an automatic way to populate the database and deal with missing data.

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CONFERENCES PROCEEDINGS

Ange-Lionel Toba, Mamadou Seck, and Issakar Ngatang (2018). Gaming and Simulation for Energy System Infrastructure: A Case of the Power Grid System. 2018 Spring Simulation Conference, Society for Modeling & Simulation International. Baltimore, MD.

Matthew Amissah, **Ange-Lionel Toba**, Holly Handley, and Mamadou Seck (2018). Towards a Framework For Executable Systems Modeling: An Executable Systems Modeling Language (ESYSML). 2018 Spring Simulation Conference, Society for Modeling & Simulation International. Baltimore, MD.

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JOURNAL ARTICLES

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