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Institutions: Katholieke Universiteit Leuven

Published on: 01 Feb 2021 - Renewable & Sustainable Energy Reviews (Pergamon)

Topics: Investment decisions and Investment (macroeconomics)

Department of Mechanical Engineering
Energy Systems Integration & Modeling Group

Energy Systems Integration & Modeling Group Working Paper Series
No. ESIM2020-17

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Last update: October 21, 2020

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Abstract

Long-term electric power system planning models are frequently used to provide policy support in the context of the ongoing transition towards a low-carbon electric power system. In a liberalized market, this transition relies on generation company investment decisions. These decisions are shaped by both economic and behavioral factors. Agent-based modeling allows the incorporation of both factors in the description of the investment decision making process. Nevertheless, there are several challenges associated with the design of agent-based models such as the definition of the model structure and its lack of transparency. In this study, we aim to increase the transparency of investment decision making algorithms by shedding light on how implicit assumptions of the price projection methods used in these algorithms impact model results. To achieve this goal, we developed a core long-term agent-based model to assess different investment decision making algorithms from the literature and we introduced a novel price projection method based on optimization modeling. Our results show that investment decisions vary enormously depending on the assumptions and parameters used in investment decision making algorithms. We also found that our proposed price projection method is robust to parametric deviations. Thus, the proposed investment decision making algorithm enables agent-based modelers to mitigate the potential impacts of hidden implicit assumptions.

Keywords:

Investment decision making algorithms; agent-based simulation modeling; generation expansion planning; optimization modeling

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Nomenclature

j	Type of technologies
y	Year
d	Day
h	Hour
Δt	Time step (typically one hour) (*h*)
r	Interest rate
$f_{j,y}$	Fixed cost of technology type *j* in year *y* (€/MW/a)
$G_{j,y}$	The installed capacity of technology type *j* in year *y* (MW)
W_d	The weight of representative day *d*
$\gamma_{j,h}$	The capacity factor of technology type *j* in hour *h*
$v_{j,y,d,h}$	The variable cost of technology type *j* in year *y* on representative day *d* at hour *h* (€/MWh)
$g_{j,y,d,h}$	The actual power output of technology type *j* in year *y* on representative day *d* at hour *h* (MW)
$p_{y,d,h}$	The market price in year *y* on representative day *d* at hour *h* (€/MWh)
$ll_{y,d,h}$	Load loss in year *y* on representative day *d* at hour *h* (MWh)
$VoLL$	Value of lost load (€/MWh)
f_j^{CAPEX}	The annual investment cost of technology type *j* (€/MW/a)
P_j	The principal of technology type *j* (€/MW)
$f_{j,y}^{O\&M}$	The fixed operational & maintenance cost of technology type *j* in year *y* (€/MW/a)
$v_{j,y,d,h}^{O\&M}$	Variable operational & cost of technology type *j* in year *y* on representative day *d* at hour *h* (€/MWh)
$v_{j,y,d,h}^{fuel}$	Fuel price of technology type *j* in year *y* on representative day *d* at hour *h* (€/MWh)
μ_j	The energy conversion efficiency of technology type *j*
$L_{y,d,h}$	The load in year *y* on representative day *d* at hour *h* (MWh)
$inv_{j,y}$	The investment in technology type *j* in year *y* (MW)
$dec_{j,y}$	The decommissioning in technology type *j* in year *y* (MW)
n_j	The lifetime of technology type *j*

1. Introduction

In a liberalized electricity market, the ongoing energy system transition towards a low-carbon electric power system is highly dependent on investment decisions. Many studies have shown that investors' decisions are not only driven by economic factors [1], [2] . Actors' behaviors, values, and strategies as well as policies, regulations, and markets also shape the electric power system transition [3], [4]. Empirical studies based on interviews with over a hundred industry experts have revealed that investors' renewable energy technical know-how and a priori beliefs on the technical effectiveness play much more important roles than technical information in investment decision making [5], [6]. Other empirical studies highlighted the importance of technology preferences, prior investments, and financial status to explain differences in investments. Bergek *et al.* presented empirical evidence showing that renewable energy investments are made by a heterogeneous group of investors and their investments vary among investor types [7]. Accounting for these above-mentioned factors calls for modeling techniques capable of representing investors and their decision-making process explicitly.

Agent-based modeling allows the incorporation of both economic and non-economic factors in the description of the investment decision making process [8], [9]. Nevertheless, despite numerous benefits, there are several challenges associated with the design of agent-based models such as the definition of the model structure and its lack of transparency. In this study, we aim to increase the transparency of investment decision making algorithms by shedding light on how implicit assumptions of the price projection methods used in these algorithms impact model results.

An investment decision making algorithm in a long-term agent-based model typically consists of three steps. First, projections are made regarding the short-run profits/rents (i.e., the revenues subtracted by the operational expenditures) that can be obtained for potential investments. Second, these projections are used to evaluate the profitability of potential investments. The profitability is typically expressed by calculating common metrics, such as the net present value (NPV) or the internal rate of return (IRR). In a third and final step, the most profitable investment, if any, is selected. This process is typically repeated until none of the agents is willing to invest anymore. The main challenge that these models face resides in the first step, i.e., designing a suitable method that allows the agents to make projections of future revenue/price streams. Whereas existing agent-based models are aligned on the metrics and criteria used for making an investment decision (e.g., a non-negative NPV or a minimum IRR), the methods used in different existing long-term agent-based models to project future prices or revenue streams vary strongly (see Section 3.2 for a detailed description).

Therefore, this study aims to analyze different price projection methods adopted in existing long-term agent-based electric power system simulation models. Furthermore, a price projection method based on optimization modeling is proposed and evaluated against existing price projection methods on a level playing field – a core long-term agent-based simulation model. This paper contributes to the literature in the following ways:

i. The price projection methods in existing long-term agent-based electric power system simulation models are reviewed and compared.
ii. The impacts of the methods used to project future prices/revenue streams on the outcome of long-term agent-based models are assessed. Specific attention is given to both the influence of (agent-level) price projection methods on the (system-level) simulation results and the ability of price projection methods to take specific scenario-related information into account.
iii. A price projection method based on optimization modeling is proposed. The proposed novel method provides a theoretical benchmark for further extension of the long-term agent-based model and allows combining the transparency of optimization models with the flexibility of agent-based models to consider behavioral aspects.

The remainder of this paper is organized as follows. Section 2 reviews the development and application of agent-based modeling in the context of electric power systems, specific attention is paid to long-term agent-based models. Section 3 introduces the methods used to carry out the analysis. This section starts with introducing the core long-term agent-based model, followed by detailed descriptions of existing and our proposed price projection methods. Next, Section 4 presents the key data and assumptions adopted in the proof-of-concept case study. Section 5 discusses the results generated by applying different price projection methods. Finally, the conclusions are drawn in Section 6.

2. Literature survey of agent-based models

Over the past decades, agent-based modeling has been used to answer multiple types of research questions in the context of electric power systems. Overall, two sets of agent-based models can be identified: short-term agent-based models and long-term agent-based models. These two types of agent-based models are often used for different purposes and the focus of this paper is on long-term agent-based models. A classification of agent-based models and their applications/capabilities are summarized in Table. 1.

Table 1. Summary of agent-based models used in the context of electric power systems.

Classification	**Key agent decision**	**Key modeling purposes**	**Example(s)**
Short-term agent-based models	Bidding strategies	Market efficiency w.r.t. market designs.	[10]–[12]
		Influence of market power exercise.	[13], [14]
		Bidding strategies and their resulting impact considering technical constraints, cross border trading and demand response.	[12], [13], [15]–[17]
Long-term agent-based models	Investment decision making	Policy evaluation (e.g. renewable subsidies)	[18], [19]
		Energy system transition w.r.t. market designs	[20]–[23]
		The influence of agents' bounded rational behaviors in the long-run	[24], [25]

Short-term agent-based models are mainly used to study the bidding game in a market under different market designs and the resulting market efficiency or exercise of market power. A comprehensive review of short-term agent-based models can be found in [26], [27]. Hereunder, some of the key studies on short-term agent-based models will be briefly reviewed. The earliest applications of agent-based modeling in electricity markets date back to the late 1990s where there was a global trend of liberalizing electricity markets. Agent-based modeling was identified as a proper method to study the market effectiveness under different market designs, as it allowed relaxing assumptions such as stable market equilibria and price-taking agents. The earliest studies evaluated the market design in two dimensions: market clearing frequency and pricing mechanisms [10], [11]. These earlier models are relatively abstract and built upon assumptions such as profit-maximizing agents, inelastic demand, and congestion-free systems. Later, other researchers contributed to the community by extending the abstract model in different directions to answer research questions related to market outcomes under the influences of grid constraints [12], [15], unit commitment constraints [16], cross border trading [13] and demand response [17].

Unlike short-term agent-based models that focus on the outcome of spot markets, long-term agent-based models are developed to study the electric power system transition with a time scale varying from years to decades. These studies are usually performed to assess the influence of specific factors such as renewable energy support design [18], CO_2 market design [28], capacity remuneration mechanisms [20]–[22], and technological preferences [24] on the evolution of the system.

In the past decades, a limited number of agent-based modeling frameworks have incorporated investment decision making at the agent level, for instance PowerACE [29], [30], AMIRIS [31], EMCAS [32], [33] and EMLab [23], [34], [35]. PowerACE is an agent-based modeling framework developed to analyze the impact of different market designs (e.g. energy-only market, capacity remuneration mechanisms) and policy measures on investment in renewable energy sources and their contribution to the security of supply on national and European level [30]. The model aims at coupling different markets (spot market, forward market, CO_2 market and reserve market) and has been utilized to address various research questions such as the influence of renewables on spot market prices [36], the economic performance of CO_2 market design [37] and the impact of a soft loan on renewable generation expansion [19]. AMIRIS (Agent-based Model for the Integration of Renewables Into the Power System) is a policy design tool used to foster the integration of renewable energy sources into the electricity market. The model is designed to study different renewable energy trading schemes, with specific attention paid to evaluating the effectiveness of a direct marketing policy[1] against the inefficient (yet effective) feed-in-tariff subsidies. To compare the policy effectiveness, the power producer agents are provided with five different business models and the outcomes can be compared [31]. EMCAS (Electricity Market Complex Adaptive Systems) was originally designed without investment decision making module but rather aims to simulate agents' behavior in the spot market. The original EMCAS consists of generation company agents, transmission system operator agents, consumer agents and regulator agents. The learning capabilities of agents are provided by genetic algorithms[2]. With the help of these different types of agents, the model is capable of studying various market organizations such as locational marginal pricing [38], congestions charges [39], bilateral contracts [40] and ancillary service markets [33]. Later, the EMCAS framework has been extended to be capable of studying long-term generation expansion [32]. EMLab (Energy Modeling Laboratory) is a long-term agent-based modeling framework designed to assess the effect of different policy instruments and market designs. These effects are reflected in the form of the aggregation of generation companies' investment decisions. Hence, the main agents in the model are the electricity generation companies and these agents interact mainly in electricity and CO_2 markets [34], [35]. As a long-term agent-based electric power system model with a minimal time step of one year, EMLab is suitable for capturing factors that influence the system evolution in a time span of years (or even decades) such as capacity mechanisms [22] and emission trading [28]. In [23], the author validated the EMLab model using sensitivity analyses from multiple aspects: theoretical and empirical. From the theoretical viewpoint, the dynamic behavior of the model and trend of producer profits (as the installed capacity approaches the load peak) are tested. Empirically, the model has been validated by comparing the model output to historical prices.

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[1] The details of the direct marketing scheme can be found in [50]. Overall, this direct marketing strategy grant freedom to wind turbine operators to be able to have a monthly choice to switch between trading in wholesale market and receiving a fixed feed-in tariff.

[2] Genetic algorithms are a set of machine learning algorithms which are used to search for the optimal solution of a problem. The term "genetic" refers to the evolutionary searching manner which imitates the evolution processes in nature: selection, crossover and mutation. We refer interested readers to [51] for a comprehensive explanation of genetic algorithms.

3. Methods

To effectively assess the influence of price projection methods on the simulation results, a core long-term agent-based modeling framework is developed and different price projection methods are deployed in its investment decision making algorithm, while keeping all other modeling settings constant. The core agent-based modeling framework is further stripped of distinctive features such as behavioral aspects. That is, in this analysis, we assume all agents to be fully rational, forward-looking price takers. Moreover, we assume that exogenous inputs such as fuel prices and technological costs remain constant. Using this set of assumptions allows obtaining a well-defined benchmark, i.e., the long-run equilibrium serves as a reference solution. More specifically, under this set of assumptions, the agent-based model should converge to the long-run equilibrium[3]. The number of converging milestone years required to converge varies from case to case, in general, it takes around 4 milestone years. This is mainly due to that, after the 3rd milestone year, all initial capacity mixes are fully decommissioned. Deviations from this long-run equilibrium can then be interpreted as impacts of the price projection method used. Note that the aim of using the long-run equilibrium as a reference is to assess possible impacts of price projection methods. The agent-based model was implemented in Julia programming language[4].

In the rest of this section, the formulation of the core long-term agent-based model and the different price projection methods analyzed in this study are described in detailed. The description of the core long-term agent-based model follows the ODD (Overview, Design concepts and Details) protocol as proposed by Grimm *et al.* [41].

3.1 Core agent-based simulation model formulation

3.1.1 Overview

3.1.1.1 Purpose

The purpose of the core long-term agent-based model is to analyze different investment decision making algorithms. This is achieved by deploying different price projection methods in its investment decision making algorithm, while keeping all other modeling settings constant.

3.1.1.2 Entities, state variables and scales

Three types of agents (entities) are considered in the core long-term agent-based model: generation companies, the market operator and consumers. The main characteristic of a generation company agent is its technology portfolio. The state variable of a market operator is the market electricity price. Consumers are characterized by their load profiles.

As a long-term model, the simulation covers several decades while the time resolution is one hour. Thus, two key concepts are introduced to couple the long-term planning (with a time span of decades) with the short-term operation (with hourly resolution): representative days and milestone years. Fig. 1 shows an exemplary scheme of representative days and milestone years. Intuitively, representative days seek to reduce the actual days in a year by finding a certain number of days and their corresponding weights that

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[3] Note that depending on the price projection method used, the equilibrium computed in the agent-based model does not necessarily converge to a single value but rather revolves dynamically around the equilibrium. In such a case, the average of the dynamic equilibrium is considered as the equilibrium reached by an agent-based model.

[4] The agent-based model is accessible via: https://github.com/zhenmin1993/ELDEST-ABM

minimize the deviation from the full hourly profiles. These profiles include load and intermittent sources such as wind and solar PV. The method of determining representative days are based on [42], in which the boundary days (i.e. peak and minimum load days) are appropriately considered. The resulting reduced load duration curve in contrast with the original load duration curve is shown in Appendix I.

Without loss of generality, the introduction of milestone years (MYs) is equivalent to the assumption that the system capacity mix will remain unchanged within a certain period of time, i.e., new investments or decommissioning can only happen in certain milestone years. Moreover, new investments are considered to be immediately available from the corresponding milestone year.

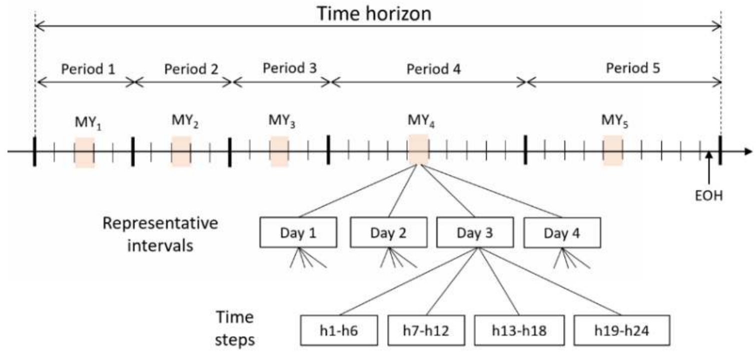


Fig. 1. An example of the temporal representation via representative days [43].

3.1.1.3 Process overview and scheduling

As indicated by the rectangles in Fig. 2, four main processes are executed in our core agent-based model: bidding in the spot market, determination of the market price, decommissioning of generators and investment in new capacity. The narrative of the core agent-based model is as follows. The bidding process in the spot market is carried out by the energy producers and all generators are assumed to bid their marginal costs[5]. Then, the market operator determines the market price by maximizing social welfare. When a milestone year is reached, generation companies first decommission generation units that have reached their lifetimes, followed by an investment process where generation companies make investment decisions sequentially. The investment process is further divided into investment rounds. During each round, each generation company is allowed to invest only once and in one generation unit. The size of a generation unit is fixed and set in a manner that all agents have approximately equal chances of being the first investor in the corresponding investment process, hence the influence of the first-mover advantage can be mitigated. The investment process is terminated when none of the generation companies has invested in the last round, i.e. no generation companies is still willing to invest anymore. It is assumed that preceding generation companies' investment decisions are known by the subsequent generation companies.

[5] Depending on the purpose of the research, this can easily be changed if desirable.

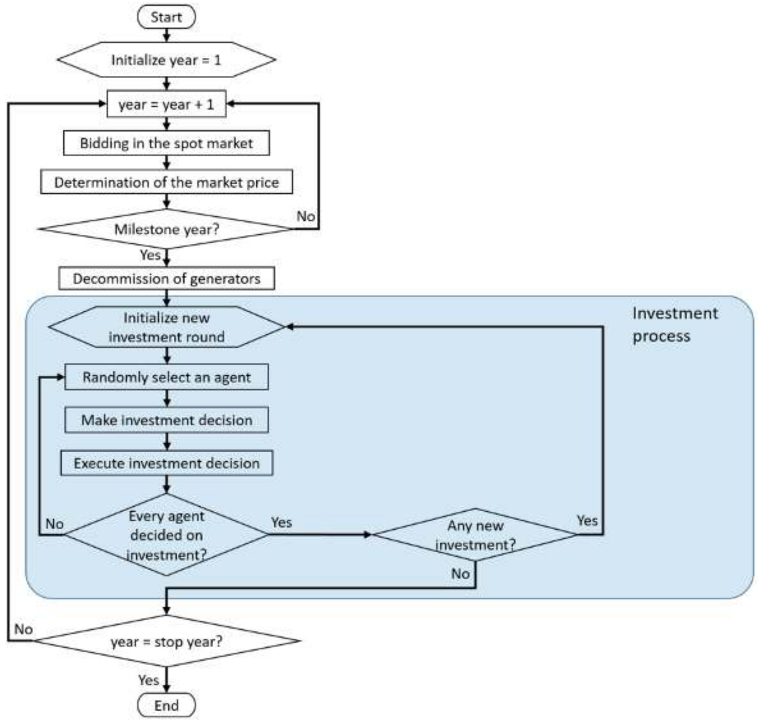


Fig. 2. Flowchart of the core long-term agent-based model.

During the investment decision making process, the profitability of all types of technologies are determined by calculating their NPVs.

3.1.2 Design concepts

- Basic principle: the principle applied in the model is the rational choice theory. This theory is used to describe decision making on both spot market bidding and new capacity investments.
- Emergence: An important emergent phenomenon in this study is the resulting capacity mix. Other emergent phenomena include the day-ahead market prices and the annual loss of load hours.
- Adaptation/Prediction: generation companies adapt their investment strategies based on future day-ahead market price projections. Evaluating the generation of these projections is one of the key contributions of this study.
- Objective: the objective of the generation companies is to optimize their generation portfolio to maximize profit by investing in new power plants.
- Learning: in this core long-term agent-based model, the learning capability has been stripped to simplify the analyses.
- Sensing: agents are assumed to know without uncertainty the preceding generation companies' investment decisions.
- Interaction: generation companies interact with each other indirectly through the price signals in the day-ahead market. That is, each newly installed power plant will lower the market price, therefore squeeze the profit margin of new investment.
- Stochasticity: the order of how generation companies carry out the investment is random.
- Observation: the key observation in this study is the system capacity mix, which reflects the impacts of agent-level investment decision making algorithms on system level. Agent level observations such

as generation portfolios are out of the scope of this study because the generation companies are assumed to be homogeneous.

3.1.3 Details

3.1.3.1 Initialization

- Initialization of existing capacity mix
  The model is initialized with a uniformly distributed existing capacity mix in the system, i.e. different types of technologies occupy the same amount of market share. Note that this initialization aims to deviate from the long-run equilibrium solution to ensure that reaching this equilibrium is not a result of the initial capacity mix.
- Initialization of generation company agents
  The model is initialized with 5 generation company agents and the existing capacity mix is assigned to these generation companies randomly. In this study, the initialization of generation companies will not change the results and conclusions as they are homogeneous.

3.1.3.2 Input data

In this study, the Belgian electric power system load data[6] (with hourly resolution) of the year 2015 is used. A Value of Lost Load (VoLL) of 3000 €/MWh and an interest rate of 5% are also used. To simplify the analyses, this study only considers highly stylized dispatchable technologies, namely base-load, mid-load and peak-load technologies. These technologies resemble respectively nuclear, coal and gas power plants whose techno-economic characteristics are based on the collected data in [44]. The techno-economic characteristics of these technologies are shown in Table 2.

Table 2. Techno-economic characteristics for the considered technologies.

Technology	Size of one unit (MW)	Lifetime (year)	VOM (€/MWh)	Fuel price (€/MWh)	Efficiency	FOM (€/kW/a)	Capital cost (€/kW)
Base-load	100	20	5	3	0.4	80	3000
Mid-load	100	20	4	15	0.48	40	1200
Peak-load	100	20	4	25	0.6	17	800

3.1.3.3 Submodels

The algorithm that describes the investment in new power plants consists of three steps. This investment decision making algorithm is followed by every single generation company. First, market conditions regarding the future electric power system are derived by taking capacity mix evolution, fuel prices and load data into consideration. Second, the future market condition is used to project future market prices. Different price projection methods are elaborated in Section 3.2. Third, the profitability of each candidate power plant is assessed by calculating its NPV. Finally, the power plant that renders the highest NPV is selected. The NPV calculation takes into account the expected revenue, the expected cost, and the

[6] The data is publicly accessible on the website of ELIA (Belgian transmission system operator). Link: http://www.elia.be/en/grid-data/data-download.

discount factor (representing the minimal expected rate of return). The formula to calculate NPV is shown in Eq. (1):

$$NPV_j = \sum_y \left(\frac{1}{(1+r)^y} \left(\left(-f_{j,y} \cdot G_{j,y} \right) + \left(\sum_d \sum_h W_{y,d} \cdot \gamma_{j,y,d,h} \cdot g_{j,y,d,h} \cdot \left(p_{y,d,h} - v_{j,y,d,h} \right) \right) \right) \right) \tag{1}$$

where r denotes the annual interest rate and $\gamma_{j,y,d,h}$ represent the capacity factors.

The fixed cost term $f_{j,y}$, being independent of the actual electricity generation $g_{j,y,d,h}$, is the sum of the annualized investment cost f_j^{CAPEX} and the fixed operation and maintenance (FOM) cost of the corresponding technology $f_j^{O\&M}$. Mathematically, the fixed costs of each installed generation unit calculated as in Eq. (2):

$$f_{j,y} = f_j^{O\&M} + f_j^{CAPEX},\ \forall j \in J, \forall y \in Y \tag{2}$$

where the investment cost is calculated with Eq. (3):

$$f_j^{CAPEX} = P_j \cdot \frac{r \cdot (1+r)^{n_j}}{(1+r)^{n_j} - 1}, \forall j \in J \tag{3}$$

The variable cost term $v_{j,y,d,h}$, calculated via Eq. (4), is dependent on the actual electricity generation and consist of fuel costs (plus emission costs and taxes) $v_{j,y,d,h}^{fuel}/\mu_j$ and variable operations and maintenance costs (VOM) $v_{j,y,d,h}^{O\&M}$.

$$v_{j,y,d,h} = v_{j,y,d,h}^{O\&M} + \frac{v_{j,y,d,h}^{fuel}}{\mu_j},\ \forall j \in J, \forall y \in Y, \forall d \in D, \forall h \in H \tag{4}$$

The key assumptions that underpin the model structure are listed below[7]:

- The load data is assumed to remain unchanged and repeated every year. For each hour, the load is assumed to be inelastic.
- The techno-economic characteristics for all technologies are assumed to be constant over the whole simulation period.
- The selection and corresponding weights of the representative days are assumed to remain unchanged in the future.
- Generation company agents' investment decisions are not subject to budget constraints.

Note that these assumptions are deployed in this theoretical study that mainly focuses on methodological analyses, and they are essential to enhance the transparency of the analyses. If the model is to be used for a case-specific analysis, these assumptions can be relaxed.

3.2 The architecture of different price projection methods

[7] Note that these assumptions are only essential for this specific theoretical study. One can change these assumptions accordingly if the model is used for case-specific analyses.

In existing long-term agent-based modeling frameworks, two different types of price projection methods can be identified: exogenous price projection methods and endogenous price projection methods. Each type can be further differentiated by the form of essential information provided as input to the corresponding method. Table 3 presents an overview of price projection methods adopted in existing long-term agent-based modeling frameworks.

Table 3. Summary of price projection methods in existing long-term agent-based modeling frameworks.

Classification		**Short description of the price projection methods**	**Example(s)**
Exogenous	Exo. 1	Price projection based on the information provided by market participants.	[31]
	Exo. 2	Virtual market clearing with exogenous capacity mix projections with existing reports as input.	[29], [45]
Endogenous	Endo. 1	Virtual market clearing assuming zero future investments.	[24], [35]
	Endo. 2	Virtual market clearing based on an endogenously established capacity mix projection. The uncertainties of competitors' future investments are exogenous and represented via a scenario tree.	[32]

One can distinguish from Table 3 that both types of existing price projection methods rely on a so-called *virtual market clearing simulation module*. This module determines projections of future electricity prices and operating hours for different investment options by combining the projections of the future capacity mix with fuel prices, demand and technological information. Although the virtual market clearing modules are formulated (and named) differently in these referenced frameworks, they can all be interpreted as a merit-order based, supply-demand matching market clearing algorithm.

We build a generalized merit-order based virtual market clearing simulation module, which is shown in Fig. 3. In the virtual market clearing simulation process, the market is cleared each time step based on the capacity mix projection over a *look-ahead horizon.* This look-ahead horizon parameter determines how far in the future an agent can have access to information when an investment object is evaluated. This parameter has been named as "reference year time horizon" and "forecast period" in [35] and [32], respectively.

Given the similarities of how future information is processed, important differences exist in terms of how future capacity mixes are projected. In the following, existing price projection methods will be described in detail, with special attention paid to capacity mix projection composition. A novel (endogenous) price projection method is also introduced.

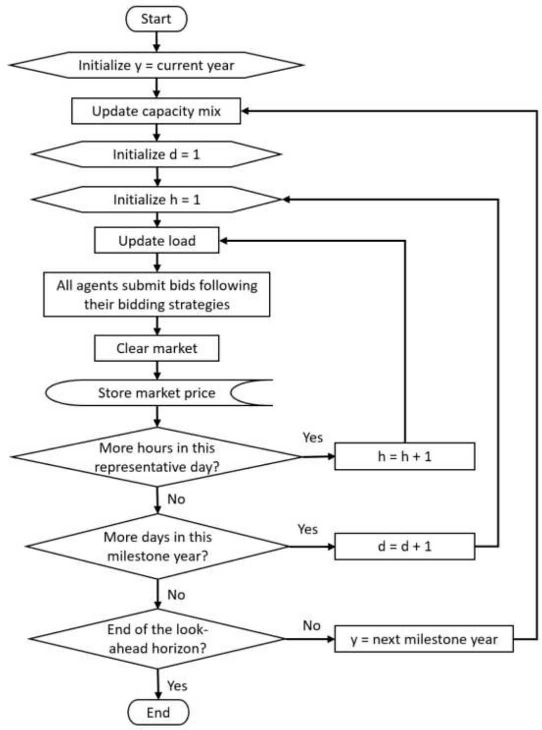


Fig. 3. Virtual market clearing simulation.

3.2.1 Exogenous price projection methods

Exogenous price projection methods rely on information about the future system from sources that are independent of the model itself. This information usually appears in one of two forms: future electricity prices or the evolution of the future capacity mix.

Projections of future electricity price information can be obtained in various ways. As an example, future electricity prices can be obtained by extrapolating past electricity prices using pattern recognition methods, as in [46]. A future capacity mix is typically drawn from third-party reports or research findings. With this information, the agents can run a virtual market clearing simulation module to retrieve expected future revenues and infra-marginal rents.

Concerning the price projection methods in existing agent-based modeling frameworks, the Exo. 1 price projection method retrieves future price information directly from interviews of market participants. The Exo. 2 electricity price projection method divides future electricity prices into two intervals: the first five years and the further future. During the first five years, it is assumed that the electricity price is the same as the spot market price in the current year. In the further future, the electricity price is calculated based on the capacity mix projection in a published report.

Despite the relatively straightforward implementation process, there are clear limitations of exogenous price projection methods. First, the modeling results are fully driven by the exogenously determined capacity mix/price projections. That is, the projections (and hence the decisions) of an agent are always in line with the exogenous input, regardless of the actual investment decisions made earlier by other agents. Therefore, the decisions taken by the agents during the simulation do not impact the decisions taken by other agents. In reality, however, there are strong interlinkages. For instance, the market value of wind generations tends to decrease significantly with the total installed wind power capacity. Second, relying on exogenous capacity mix/price projections data results in loss of flexibility in establishing case-specific scenarios. That is, one is restricted to using data from existing reports/surveys. In addition, the lack of interaction among agents results in loss of flexibility in terms of capturing some factors such as social influence[8] and endogenous risk perceptions.

3.2.2 Endogenous price projection methods

As the name implies, in endogenous price projection methods, the agents endogenously project future prices (and corresponding revenues and infra-marginal rents) during the simulation, i.e. the user does not need to supply (all) direct information regarding future electricity prices or the future capacity mix evolution.

Examples of agent-based modeling frameworks that have adopted endogenous price projection methods include for instance [24], [32], [35]. In these references, the price projection method generally consists of two steps. In the first step, projections are made regarding the future capacity mix. In the second step, the capacity mix projections are used as an input in the virtual market clearing simulation module.

The Endo. 1 price projection method is shown in Fig. 4a. Here, agents project the capacity mix in a given future year by starting from the existing capacity mix and adding the already announced or built new capacities (i.e., the investment decisions made by other agents during the course of the simulation) and subtracting the capacities reaching life expectancies before that given year. Although this approach seems reasonable at first sight, in this method the agents implicitly assume that, when projecting the prices in a given future year, no new investment decisions will happen between the current model year and a given future year. Given that these future investments make up a bigger share of the capacity mix as one looks further into the future (as a result of decommissioning of existing plants), this method has its limitations for projecting revenue streams further into the future. For this reason, this method henceforth will be referred to as "*myopic agents*". The term "myopic" refers to an agent being short-sighted in terms of the information being considered regarding future market conditions. For this method, the choice of the *look-ahead horizon* could substantially influence the resulting macro-system-level capacity mix evolution. As will be shown in Section 5.1, the assumption that the agents do not anticipate investments made in future years makes the simulation results sensitive to different look-ahead horizons. In addition, this method does not allow anticipating expected changes in the capacity mix, such as the possible expectation of increasing penetration of renewable energy sources in the future electricity system.

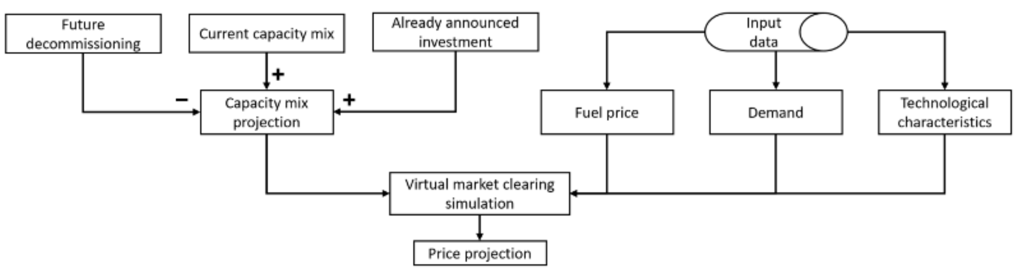
Fig. 4b represents the Endo. 2 price projection method. In addition to the information already considered by the "*myopic agents*" method, the Endo. 2 price projection method considers projections for future investments of competitors. Similar to the "*myopic agents*" method, the resulting projections of the future capacity mix are then used as inputs in the virtual market clearing simulation module to project future electricity prices. For investment decision making, the model presented in [32] includes uncertainties regarding the load growth, hydropower conditions, and the investments made by competitors in future years. The uncertainties are represented via a scenario tree, as visualized in Fig. 5. As shown on the right-hand side of Fig. 5, for each agent[9], the uncertainty regarding competitors' capacity expansion decisions

[8] In [52], social influence is defined as "change in a person's cognition, attitude, or behavior, which has its origin in another person or group."

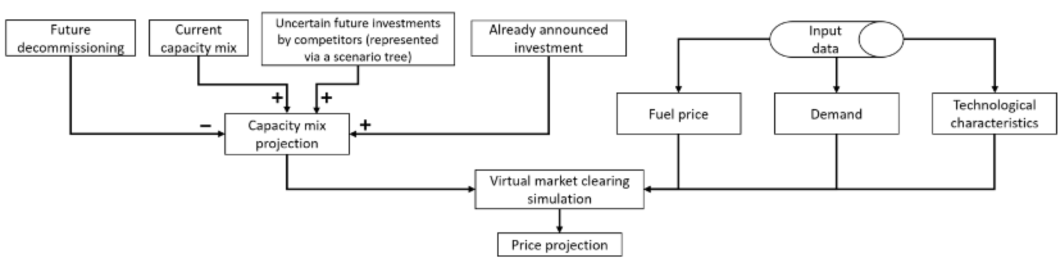
[9] As this specific study is based on a highly stylized system and mainly focuses on simulation results on system level, it is assumed that agents are homogeneous. Hence, using one scenario tree for each agent is equivalent to using one

is composed of two layers: the total capacity installed and the distribution of this capacity among different technology types. In the first layer, 3 branches varying in the total capacity installed by competitors are considered, and probabilities are assigned to each of these branches. In the second layer, each branch is further split into 3 sub-branches varying in the distribution of the total installed capacity among different technology types. It is important to note that, although the agents make endogenous projections of the future capacity mix, the projections in this method are strongly determined by exogenous inputs (i.e., the amount and distribution of capacity investments by competitors in each scenario, and the probabilities assigned to the different scenarios). Therefore, this method will be referred to as the "*exogenous scenarios for future investments*" method in the remainder of this text.

Similar to the exogenous price projection methods, this method has certain clear limitations. The primary limitation is the availability of parameters for the scenario tree, which results in loss of flexibility in establishing case-specific scenarios. Alternatively, one can carefully calibrate the scenario tree with the help of historical system capacity mix development. This type of calibration can influence the simulation results by presuming that the future capacity mix evolves in a similar manner to the past, which has been proved to be inappropriate because of various factors such as the emergence of new technologies and new entrepreneurial competitors [47]. Moreover, as the total capacity parameter determines the residual space for the corresponding agent (to invest in), the new investments in a milestone year are approximately the sum of all agents' residual space. This interplay between the parameter total capacity and the total number of agents further reduces the transparency of the agent-based model: even small deviations on exogenous inputs to agents' investment decision making can be amplified by the magnitude of the total number of agents and might strongly shape the core macro-system-level results of the model. A sensitivity analysis of the parameters of the scenario tree is carried out in Section 4.2.



a. "*Myopic agents*" price projection method.



b. "*Exogenous scenarios for future investments*" price projection method.

common scenario tree for all agents. Nevertheless, the model is designed to allow agents to have diversified scenario tree if desired.

Fig. 4. Schematic of endogenous price projection methods used in [35] (a) and [32] (b).

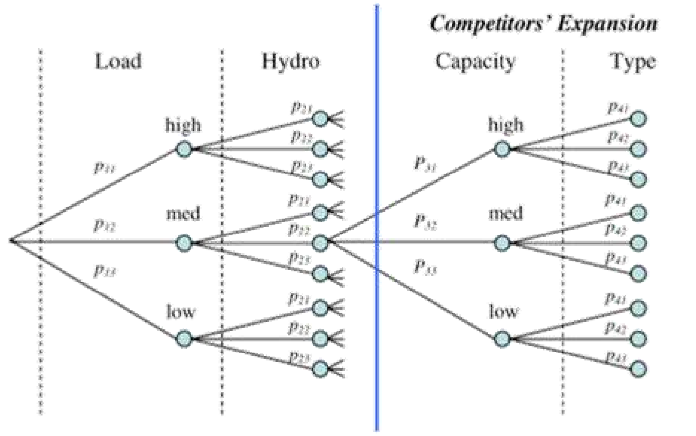


Fig. 5. Scenario tree deployed to represent the competitors' expansion [32].

3.2.3 Novel optimization-based price projection method

As presented in Fig. 6, in the novel optimization-based price projection method, the agents make price projections by solving a generation expansion planning problem (i.e., a traditional long-term electric power system optimization model). The interpretation of this method is that each agent assumes that the system capacity mix will evolve in a cost-minimizing manner when making long-term price projections[10]. For this reason, this method henceforth will be referred to as the "*cost-minimizing future investments*" method. The information regarding the current capacity mix, already announced investments and future decommissioning plans/expectations is used as input to the generation expansion planning problem. The output information from this generation expansion planning problem is twofold: shadow price and capacity mix projections. A similar method has been adopted in [48], where the authors present a price projection method assuming that the capacity mix will reach the optimal portfolio by the end of the look-ahead horizon. The price projection method interpolate prices between a myopic short-term market equilibrium and a long-term greenfield equilibrium, the price information between the short-term and the long-term equilibrium is approximated using an exponential function. One of the fundamental improvements of the (optimization-based) price projection method proposed in this study is that the price information is based on the capacity mix evolution instead of a function-based approximation, which requires additional calibrations.

Depending on the problem at hand, one could either use the shadow prices directly or could derive price forecasts starting from the capacity mix projections. Deriving price forecasts via the capacity mix projections allows considering for instance strategic behavior, negotiations for long-term bilateral contracts and/or allows increasing the level of granularities by considering different weather years or outage distributions via Monte-Carlo simulations. This provides modelers with the flexibility to capture behavioral (or other) aspects in the context of the ongoing electric power system transition. Fig. 7 illustrates how strategic bidding behavior could be captured in the price forecasts. Note that taking

[10] This assumption is equivalent to the assumption that agents assume perfect competition (i.e., all agents are price-takers have perfect information, and barriers to entry and exit are small.)

strategic behavior (e.g. market power) into consideration will potentially result in a different capacity mix projection. Hence, the “generation expansion planning” does not necessarily have to be a cost-minimization optimization problem. One of the alternatives is to use MPEC (mathematical programming with equilibrium constraints) for capacity mix projection as presented in [49], though implementing an MPEC is beyond the scope of this paper. In the bidding game model, each agent could, for instance, use a reinforcement learning algorithm to derive its optimal bidding strategy. Via the learning algorithm, agents will learn whether they can manipulate prices. This method has been proven effective in [14] to forecast market prices in the context of the New Zealand electricity market. A global overview of the long-term agent-based model with the proposed investment decision making framework and the novel price projection method is shown in Appendix II.

It is important to recall that the goal of the novel price projection method is to enable the agents to base their investment decisions on price projections that are (i) theoretically unbiased, (ii) transparent, (iii) and can be flexibly generated for a range of possible scenarios (e.g., differing in assumptions regarding evolutions of fuel cost, technological improvements, and policies). Although out of the scope of this paper, it is also important to note that the framework is sufficiently flexible to allow considering specific features typical for an agent-based model, such as the modeling of behavioral aspects.

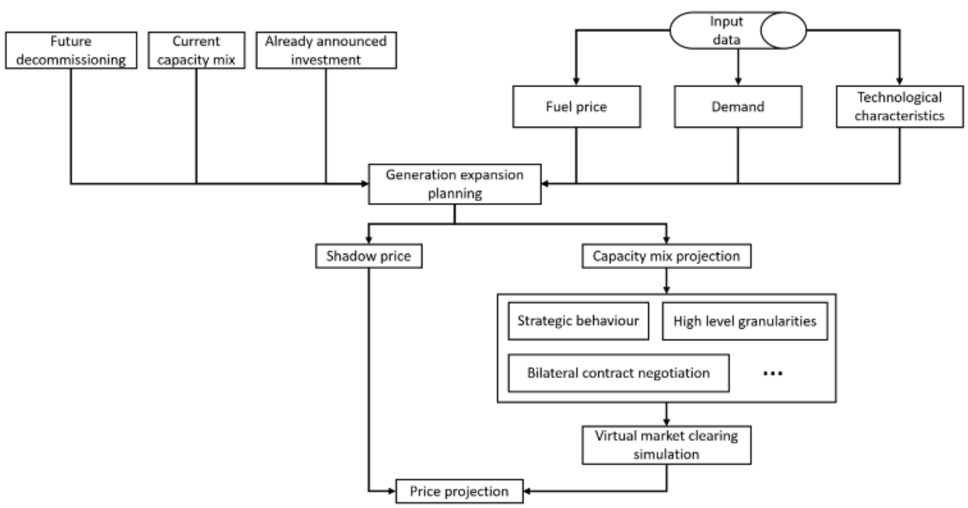


Fig. 6. Schematic of the novel proposed price projection method of each agent.

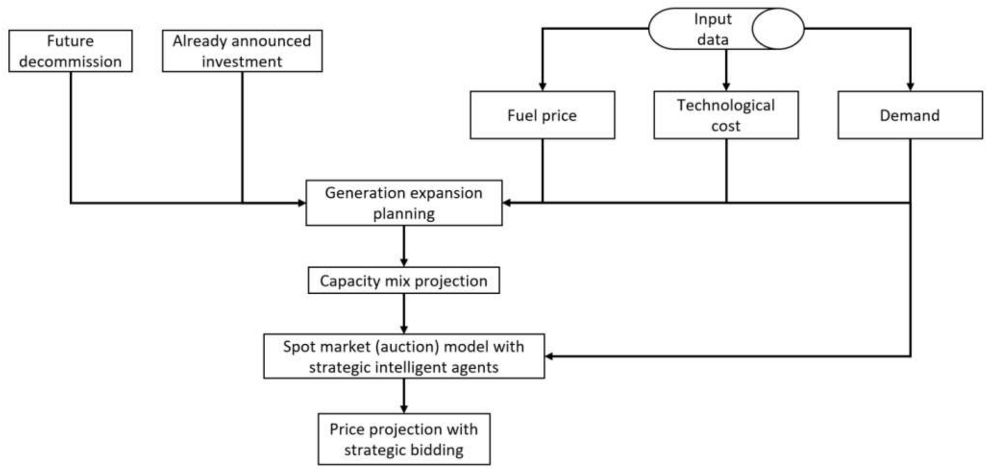


Fig. 7. An exemplary illustration of price projection taking strategic behavior into consideration.

The mathematical formulation of the generation expansion planning problem used for price projection or capacity mix projection or both is as follows. Since the optimization model will be dispatched frequently in the course of the simulation, the optimization model has been formulated in a simple manner to reduce the computational cost.

3.2.3.1 Objective function

The objective function (Eq. (5)) aims to minimize the total system cost:

$$\min_{G_{j,y}} \sum_{y}\sum_{j}\left(\left(f_{j,y}\cdot G_{j,y}\right)+\left(\sum_{d}\sum_{h} W_d\cdot v_{j,y,d,h}\cdot g_{j,y,d,h}\cdot \Delta\mathrm{t}\right)\right)+\left(VoLL\cdot\sum_{y}\sum_{d}(W_d\cdot\sum_{h} ll_{y,d,h})\right) \quad (5)$$

The two parts in the objective function represent the cost of electricity generation and the cost of load loss, respectively. The cost of electricity generation consists of fixed costs (see Eq. (2)) and variable costs (see Eq. (4)). The cost of load loss is the weighted sum of load loss over the entire optimization horizon multiplied by a fixed value of lost load value ($VoLL$).

3.2.3.2 Constraints

- Energy balance constraint: for each time step t, the summation of generators' gross output and load loss equals the total demand.

$$\textstyle\sum_{j=1}^{J}(g_{j,y,d,h}\cdot \Delta\mathrm{t})+ll_{y,d,h}=L_{y,d,h},\ \ \forall j\in J,\forall y\in Y,\forall d\in D,\forall h\in H \quad (6)$$

- Installed capacity constraint: for each year, the capacity mix is updated by adding new investment(s) and subtracting decommissioning.

$$G_{j,y}=G_{j,y-1}+inv_{j,y-1}-dec_{j,y-1},\forall j\in J,\forall y\in Y \quad (7)$$

- Decommissioning constraint: the decommissioning of technology type j in year y is the investment in technology type j in year y-nj, where nj is the lifetime of the technology.

$$dec_{j,y}=inv_{j,y-n_j},\forall j\in J,\forall y\in Y \quad (8)$$

- Generation limits: the actual power output of each type of technology is non-negative and should not exceed the installed capacity of the corresponding technology.

$$0 \leq g_{j,y,d,h} \leq G_{j,y}, \ \forall j \in J, \forall y \in Y, \forall d \in D, \forall h \in H \quad (9)$$

4. Case study set up

4.1 Key assumptions and settings of the core long-term agent-based model

Recall that this study aims to effectively assess different price projection methods. Under the assumption of perfect information and fully rational agents as well as deterministic circumstances, a well-calibrated agent-based model would be expected to reach (or at least approximate very well) the long-run equilibrium. With the goal of benchmarking the solution against the long-run equilibrium solution, it is further assumed, in addition to the assumptions adopted in Section 3.1.3.3, that all agents are fully rational, forward-looking and act as price takers. As shown in Fig. 7, this assumption can be relaxed by running the virtual market clearing simulation with strategic agents.

4.2 Configuration of the "*exogenous scenarios for future investments*" price projection method

As discussed in Section 3.2.2, it is challenging to assign appropriate values (both technology distributions and total capacities) for the scenarios representing the future investments that will be made by competitors. To study the influence of these expectations, a sensitivity analysis is performed in which the exogenous projected investments of competitors are varied both in terms of the total capacity that is expected to be added by competitors in future years as well as in terms of the distribution of technologies in which competitors are expected to invest. In terms of total capacity added, we consider competitors invest up to 85%, 90% and 95% of the load peak[11]. In terms of the technology distribution, three different cases are considered. This leads to a total of 9 possible cases for the future investments projected to be made by competitors. The parametric combinations and the corresponding tags of these 9 cases are presented in Table 4.

Table 4. Parameters considered for the expansion scenario tree.

	Distribution (Base/Mid/Peak)		
Competitors' total expansion	**0.2/0.5/0.3**	**0.3/0.2/0.5**	**0.5/0.3/0.2**
0.95	(a)	(b)	(c)
0.9	(d)	(e)	(f)
0.85	(g)	(h)	(i)

5. Results and discussion

[11] In [32], this parameter is 95% and a sensitivity analysis is performed by reducing this parameter to 90%. However, an agent-level annual investment cap restricts the development of the system capacity. Hence, to dissect the influence of this parameter, we remove the agent-level investment cap and further reduce this parameter to 85%. If this parameter is 100%, resulting system capacity mix will be empty because all agents are expecting other agents to completely fulfil the demand.

In this section, the simulation results of a long-term agent-based model with different price projection methods are compared. Specifically, the following price projection methods are considered:

i. The "*myopic agents*" method (as presented in Section 3.2.2).
ii. The "*exogenous scenarios for future investments*" method (as presented in Section 3.2.2).
iii. The "*cost-minimizing future investments*" method (as presented in Section 3.2.3).

The potential impacts of these price projection methods on micro-agent-level investment decision making algorithms are reflected at the macro-system-level capacity mix. Hence, a sensitivity analysis is performed to the corresponding key parameters of different price projection methods. As highlighted in Section 3, different price projection methods have their respective key parameters:

i. The *look-ahead horizon* in the "*myopic agents*" method and the "*cost-minimizing future investments*" method[12]
ii. The values assigned to the scenario tree in the "*exogenous scenarios for future investments*" method[13]

Fig. 8 provides an overview of the capacity mix resulting from different price projection methods and their corresponding sensitivities. The benchmark solution, as discussed in Section 3, for all simulations is the long-run equilibrium, which is computed by a generation expansion planning model that takes the same input data as the agent-based model.

The simulation results of the core agent-based model with the three price projection methods incorporated are the averaged value of the oscillations. As can be observed, the "*myopic agents*" and "*exogenous scenarios as future investments*" price projection methods are highly impacted by their corresponding key parameters. This is reflected by the substantially varied macro-system-level capacity mix. The proposed "*cost-minimizing future investments*" price projection method, on the other hand, is shown to systematically approximate the long-run equilibrium. The following sections provide a detailed analysis of each of the sensitivities considered.

[12] Scenario tree is not part of the "*cost-minimizing future investments*" method, while this method still preserves the parameter look-ahead horizon.

[13] Note that the look-ahead horizon, yet uncritical, also exists in the "*exogenous scenarios for future investments*" method. Further note that, as discussed in Section 3.2.2, although the impact of the competitors' total expansion parameter is amplified by the total number of agents and we keep the total number of agents constant in this study, similar studies can be carried out by keeping the competitors' total expansion constant and varying the total number of agents. Nevertheless, the total number of agents, in specific case studies, should be determined by the system one considers.

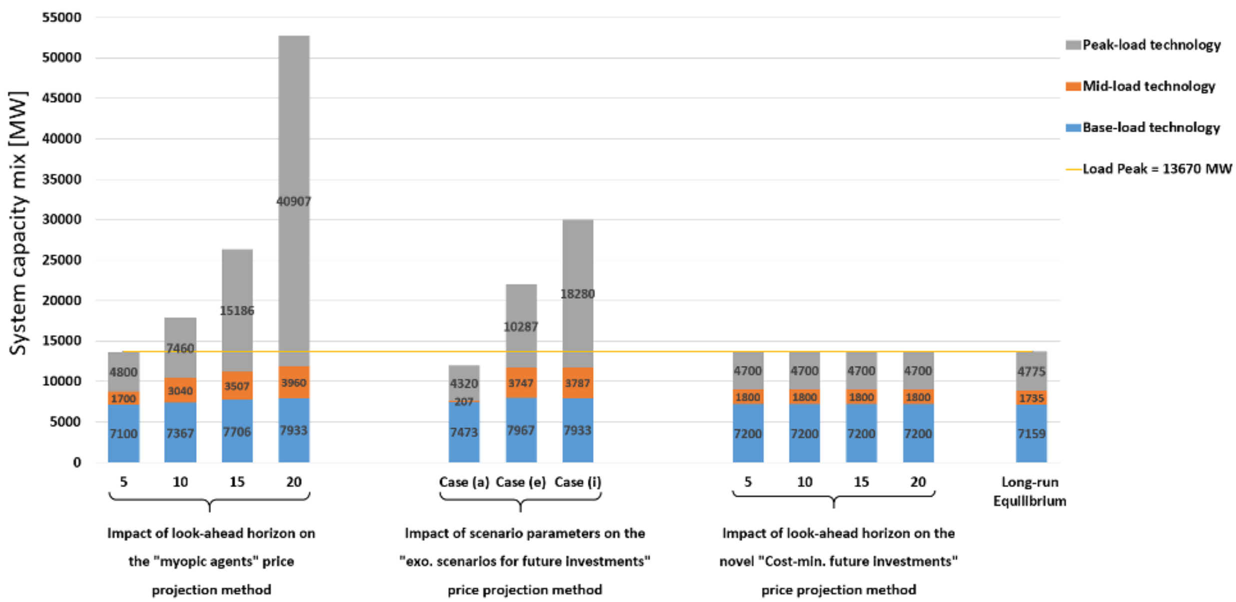


Fig. 8. Overview of the impact of key parameters of different price projection methods on the resulting system capacity. The considered price projection methods are described in Section 3.2. The cases considered for the "*exogenous scenarios for future investments*" method are presented in Table 4.

5.1 Sensitivity analysis on the look-ahead horizon

The look-ahead horizon is a key micro-agent-level parameter in investment decision making algorithms since it determines the future information that is taken into account in agents' investment decision making. A perfectly rational and forward-looking agent would base its investment decision on revenue/rent projections within the entire lifetime of the considered investment. Nevertheless, as outlined in Section 1, heterogeneous agents can have particular perceptions of the information and they can be myopic (i.e., have a limited foresight). The look-ahead horizon can be adjusted to represent possible short-sightedness of agents. Adjustments of the look-ahead horizon thus reflect a way of modeling a behavioral aspect. Note that in this work, we aim to establish a robust and theoretically unbiased core long-term agent-based model. Hence, we neglect behavioral aspects. Note also that the current modeling setting has constant fuel prices, technological costs as well as a fixed load profile (i.e., the load profile remains constant over different years in the simulation). In this setting, an agent-based model should in principle be able to approximate the long-run equilibrium on the macro-system-level regardless of the micro-level assumptions on the agents' look-ahead horizon. Therefore, under the current case study, we consider the robustness of the system capacity mix to changes in the look-ahead horizon as an important indicator of investment decision robustness. As discussed in Section 3.2.2, the look-ahead horizon is particularly important for the "*myopic agents*" price projection method, as the share of future investments in the future capacity mix grows when looking further into the future.

As shown in Fig. 8, the simulation results are highly sensitive to different look-ahead horizons when using the "*myopic agents*" price projection method. More specifically, the overinvestment grows larger as the look-ahead horizon becomes longer. Peak-load technology accounts for most of the overinvestment. The simulation results of the agent-based model with the "*cost-minimizing future investments*" price projection method are more robust under different look-ahead horizons and systematically approximate the equilibrium solution very well. This indicates that the core long-term agent-based model, with investment decision making algorithm integrated, can serve as an ideal theoretical benchmark for further extension of the model.

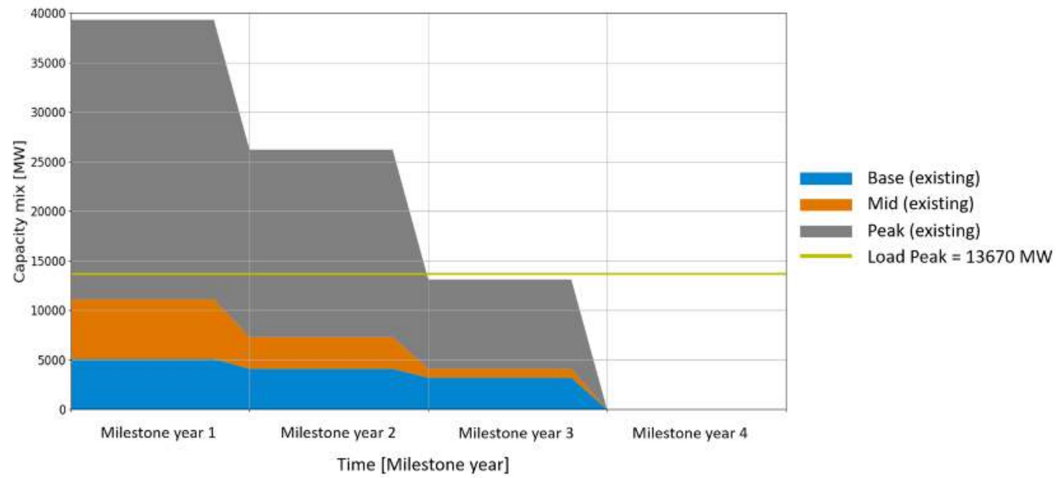
The results in Fig. 8 also show that using the "*myopic agents*" price projection method with a 5-year look-ahead horizon can approximate the long-run equilibrium. The reason is that using a 5-year look-ahead horizon means that the agents base their investment decisions only on the system status in the first milestone year, thus the observed scarcity is the recent decommissioning and no future information is considered. In a perfectly competitive market, the profit-maximizing agents will make investment decisions that fill the gap in a system cost-minimizing manner.

To shed light on why the model is sensitive to the parameter look-ahead horizon, we take the case where agents are assumed to have the longest look-ahead horizon (20 years or the lifetime of the technologies) as an example. Recall that every fifth year is a milestone year, meaning 20 years comprise 4 milestone years. With different price projection methods, the capacity mix projections of the first agent that is making an investment decision in the first investment round during a typical milestone year are plotted in Fig. 9.

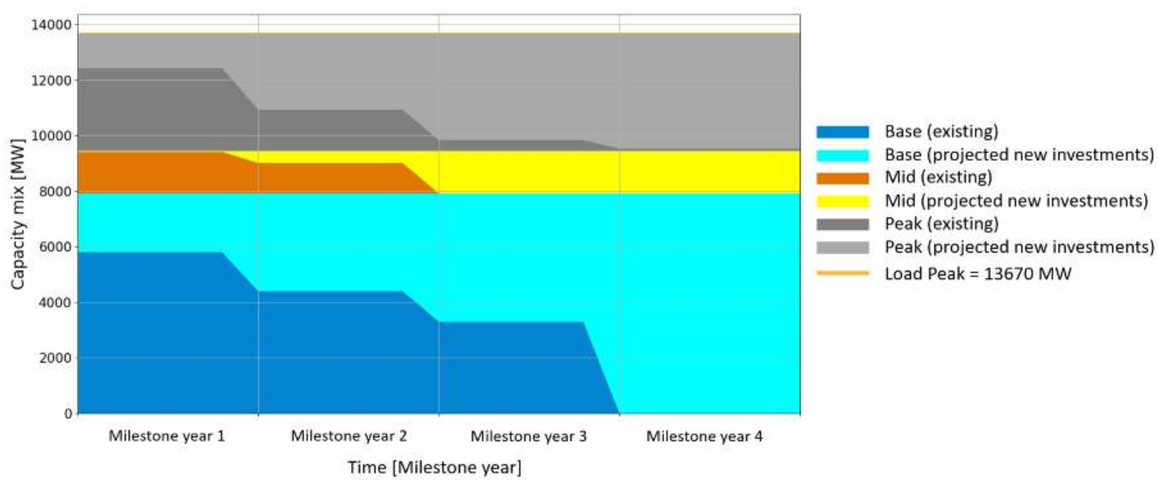
When agents make investment decisions assuming that no new investments will happen, as shown in Fig. 9a, the first agent in the first investment round will sense zero announced investment (as there is no preceding investment in this milestone year). In combination with the fact that all existing capacities will be decommissioned after three milestone years (or after 15 years), as the youngest existing capacities are the investments placed in the previous milestone year, being 5 years ago. This leads to a huge projected lack of capacity in the fourth milestone year, even though over-capacities already exist in the first milestone year. In the virtual market clearing, this lack of capacity is translated into electricity price projections corresponding to the price cap for the entire year, which is obviously not realistic. The projected high prices towards the end of the look-ahead period incentivize investments until the point that the future supply gap is almost filled. In addition, expecting supply gaps and corresponding high electricity prices only in the last 5 years means the considered investment option tends to be dispatched mainly in this period. Given this low number of projected operating hours, the technology with the lowest fixed cost is favored, which explains why peak load technology accounts for most of the overinvestment.

A number of measures can be taken to avoid or mitigate this overinvestment problem. For instance, one could force the agents to be myopic (which is used in [35] and [24]) or impose an agent-level annual investment cap (which is used in [32]). One could also consider adjusting the projected electricity prices, for instance by reducing the high prices observed towards the end of the look-ahead horizon. However, requiring agents to behave myopically to forcibly correct unintended simulation results reduces the applicability of the model (that is, only myopic investment behavior can be considered). Moreover, although introducing corrective actions such as investment caps or price adjustments does allow considering longer look-ahead horizons, it leads to secondary problems (what is a reasonable investment limit? What would be appropriate electricity prices at the end of the look-ahead horizon?) and assumptions that both might require further rectification and reduce transparency.

Fig. 9b illustrates the capacity mix foreseen by agents with the "*cost-minimizing future investments*" price projection method. In such a case, the agents have the abilities to both establish expectations on future investments and keep these expectations according to the intrinsic characteristic of the system. Furthermore, the look-ahead horizon is no longer affecting the investment decisions as the investment is no longer incentivized by the unrealistic high electricity prices that arise only in the last milestone year, but rather by the homogeneously distributed electricity prices over the entire look-ahead horizon.



a. “*Myopic agents*”.



b. “*Cost-minimizing future investments*”.

Fig. 9. Capacity mix projections of the first agent that is making an investment decision in the first investment round during a typical milestone year.

5.2 Sensitivity analysis on the values assigned to the scenario tree in the “*exogenous scenarios for future investments*” price projection method

On micro-agent-level, the expectations of agents about competitors’ expansion plan directly affect their investment decisions by altering the projections of future electricity prices. These affected investment decisions will ultimately be reflected on the macro-system-level in the form of capacity mix variations. Fig. 10 shows the resulting system capacity mixes for different cases of the competitors’ expansion projections (see Section 4.2 for a detailed description of these cases). The resulting macro-system-level capacity mix for each case is shown in Fig. 10 and summarized in Table 5.

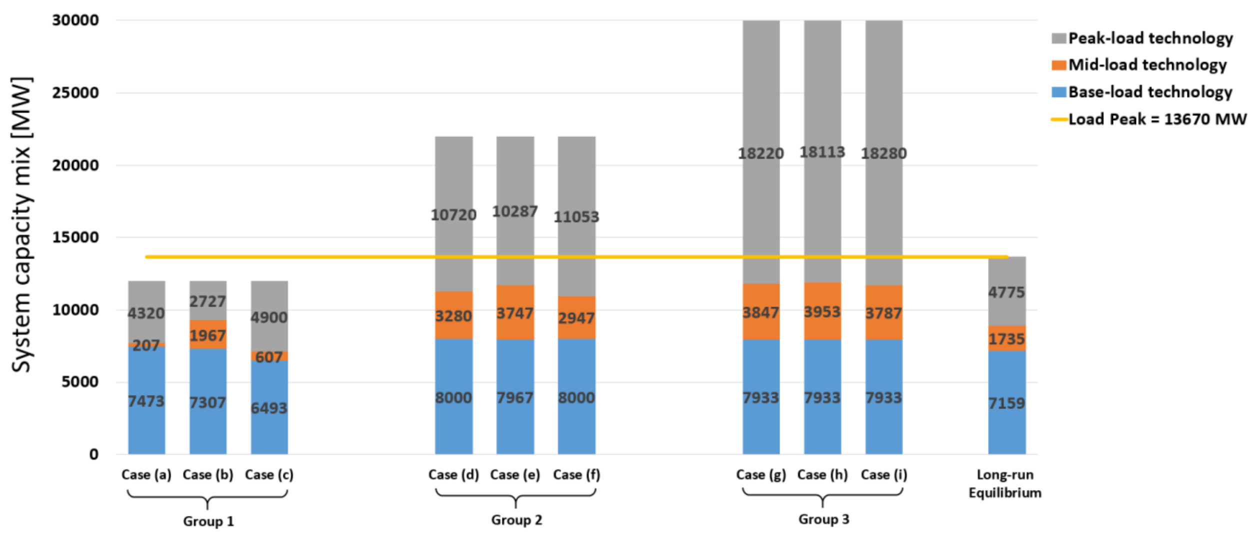


Fig. 10. System capacity mix with different competitors' expansion projections.

Table 5. Amount of different technologies in the capacity mixes (unit: MW).

	Group 1			Group 2			Group 3		
Technology	**(a)**	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**
Base-load	7473	7307	6493	8000	7967	8000	7933	7933	7933
Mid-load	207	1967	607	3280	3747	2947	3847	3953	3787
Peak-Load	4320	2727	4900	10720	10287	11053	18220	18113	18280
Total	12000	12001	12000	22000	22001	22000	30000	29999	30000

Overall, one can observe that the simulation results vary largely depending on the exogenous inputs used. First, by comparing the system capacity mix for different expectations regarding the total capacity projected to be added by competitors in the future (comparing the different capacity mix groups in Fig. 10), one can observe that decreasing the expectation on competitors' total expansion (from 95% to 90% and 85%) leads to a substantial increase in the total system capacity and vice versa. On the one hand, low expectations on competitors' total expansion lead to unrealistic high prices in the future and these high electricity prices trigger investments until the future supply gaps are filled. On the other hand, high expectations on competitors' total expansion squeeze the investments of all agents and lead to underinvestment, i.e., all of the agents lack of an investment incentive because they overestimated competitors' future investments.

Second, by comparing the different projections of the technology distribution of the future investments by competitors (comparing the capacity mixes within each group in Fig. 10), it can be seen that the assumed technology distribution can result in a considerable change in the system capacity mix. More specifically, the more a certain type of technology is expected to be invested in by competitors, the less the agents will invest in this technology, and vice versa. Consider the Group 1 of Fig. 10 as an example. As the expected proportion of future investments in peak-load technology increases from 20% to 30 % and 50%, the proportion of peak-load technology in the simulation results decreases from 40.8% to 36% and 22.7%, respectively. A similar trend also holds for investments in base-load technologies. For mid-load technologies, it is more complicated as the economic potential for investments in mid-load technologies is also strongly impacted by the projected investments in base-load and peak-load technologies.

Additionally, one can also find that as the projected total capacity installed by competitors in future years decreases (inter-Group), the technology distribution of the projected investments by competitors (intra-Group) has a smaller impact on the resulting system capacity mix. This is primarily because the influence of these expectations tends to be weaker as the expected investments become less. At the same time, as the projected competitors' investment becomes less (inter-Group), the driving factor switches from technology distribution to the total capacity added. And as a result, the macro-system-level capacity mixes tend to resemble each other. In fact, in the extreme condition (with the total expansion expectation reduced to zero), these capacity mixes converge to those of the "*myopic agents*" method.

Moreover, although different capacity distribution parameters change the capacity mix, the total amount of capacity remains constant within one total expansion level setting. That is, the total amount of installed capacity is completely driven by the setting of the expected total amount of competitors' expansion, instead of the intrinsic characteristics of the model.

5.3 Implications and limitations

The analysis above suggests that the assumptions adopted by investment decision algorithms (on agent level) can highly impact the simulation results on system level. Specifically, the system capacity mix is highly sensitive to the parameter *look-ahead horizon* when the "*myopic agents*" price projection method is used. This is due to that this method implicitly assumes no new investment will happen in the future and therefore a supply gap will arise, which triggers new investment in the agents' located milestone year (i.e. milestone year 1) to compensate for the unrealistic under-capacity in the further future. Examination on "*exogenous scenarios for future investments*" price projection method shows that, the values assigned to the scenario tree regarding competitors' investments (on agent level) is dominating the simulation results on the system level. Overall, the two layers on the scenarios tree govern different aspects of the simulation results: the total amount of installed capacity is driven by the expectation on competitors' total investment, and the share of different types of technologies are mainly influenced by the second layer of the scenario tree (i.e. how competitors' new investments are distributed among candidate technologies). As we have shown, our proposed "*cost-minimizing future investments*" price projection method requires less exogenous parameters (i.e. scenario tree) and is more robust to the parameter look-ahead horizon.

The newly proposed price projection and the analysis performed in this study, however, do have several limitations. From a methodological viewpoint, using the resulting output from a generation expansion planning problem to guide investment decision making implicitly assumes that the agents are expecting the capacity mix to evolve in a cost-minimizing manner. The electricity market, in reality, is more complicated. For example, strategic investment behavior or market imperfections can result in deviations from the perfect market outcome. One of the alternatives is to consider the MPEC (mathematical programming with equilibrium constraints) formulation of a generation expansion planning problem, which allows the inclusion of strategic investment behaviors, as presented in [49]. Moreover, note that the analysis is performed in a highly stylized electric power system where the agents are stripped of distinctive features such as behavioral factors. In reality, there exist many behavioral factors that influence investment decision making. Accounting for these factors can deviate the results from the perfect market outcomes and can mitigate the impact of the existing price projection methods' underlying assumptions on model outcomes. For instance, employing risk-averse agents can reduce the sensitivity of the parameter look-ahead horizon because the unrealistic profit in the distant future is subject to a very high discount rate. Hence, the existing price projection methods, if adequately parameterized, can also approximate empirical results.

6. Conclusion

This paper reviewed different investment decision making algorithms adopted in long-term agent-based electric power system simulation models. Furthermore, this paper compared three endogenous investment decision making algorithms by benchmarking against the long-run equilibrium. More specifically, sensitivity analyses on the assumptions adopted by the two existing investment algorithms have been carried out and compared with a novel investment decision making algorithm.

Simulation results show that, in an isolated electricity market with highly stylized modeling settings, the investment decisions made by existing investment algorithms are highly sensitive to assumptions regarding certain parameters of the investment decision making algorithms. Due to the difficulties to properly calibrate these values, the credibility and transparency of simulation results can be influenced by the selection of key parameters. Therefore, it is of great importance for modelers to be well aware of the influences imposed by these assumptions and key parameters.

Further analysis has shown that the core agent-based model – with the proposed micro-agent-level "*cost-minimizing future investments*" price projection method adopted – is robust and more transparent in the theoretical modeling settings used in this study. This core agent-based model, with the proposed price projection method integrated, enables agent-based modelers to mitigate the potential impacts of implicit assumptions (related to modeling specific behavioral aspects) and the influence of control variables (e.g., policy instruments), thereby paving the road towards transparent, unbiased, and robust long-term agent-based electric power system simulation models.

In light of the results we have presented, future work will focus on developing more elaborated investment decision making algorithms. It is of particular interest to consider risk-averse investment decision making under uncertainty and market imperfections. The uncertainties include but are not limited to load growth uncertainties, fuel price uncertainties, and policy uncertainties. The model will then be able to map from these uncertainties to price projection uncertainties, which calls for a stochastic generation expansion planning problem to generate a price projection distribution. Furthermore, future work will incorporate renewable energy sources into the modeling framework. To do so, both the NPV calculation and the price projection method have to be improved. On the one hand, regarding the NPV calculation, revenues from renewable support schemes should be further considered in addition to the fixed costs, variable costs and day-ahead market revenues On the other hand, the optimization problem will have to consider endogenously the impact of renewable support schemes. For instance, an investment subsidy can be modelled as a linear fixed revenue at each year for each type of renewable technology, this can be a one-off payment or payments that spread over several years, whereas a market-based support scheme (e.g. green certificates market), requires additional constraints to couple with the day-ahead market in a two-stage optimization problem. These future improvements to the agent-based modeling framework will be tested in a specific case study. An interesting case study, where the impact of the incorporation of renewable energy sources, agents' decision-making under uncertainty, and market imperfections on models results could be demonstrated, it is the analysis of the Belgian nuclear phase-out.

Acknowledgements

This research received funding from Fonds Wetenschappelijk Onderzoek (FWO) with grant number S006718N, and the Belgium Federal Public Service Economy, Energietransitiefonds, Neptune project.

Appendix I. Reduced load duration curve in contrast with the original load duration curve.

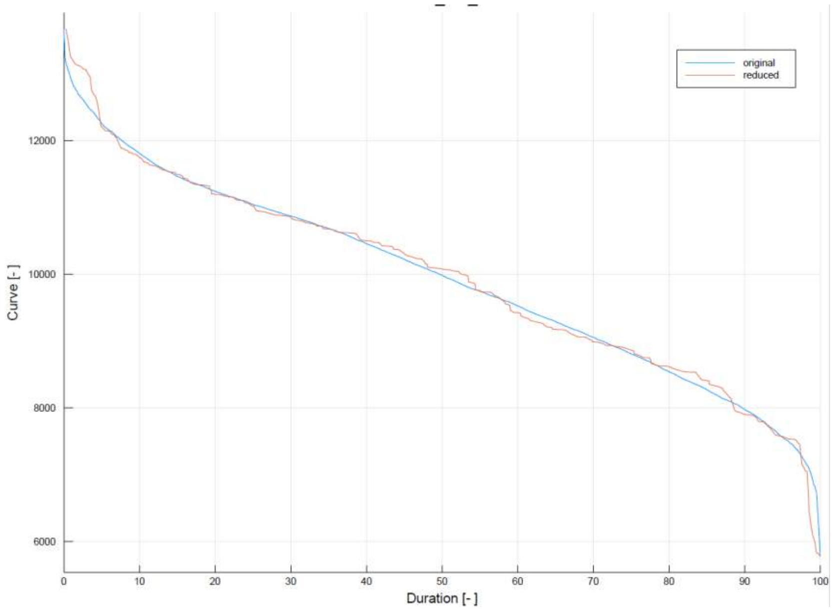


Fig. A1. Reduced load duration curve in contrast with the original load duration curve

Appendix II. Flow diagram of the agent-based model

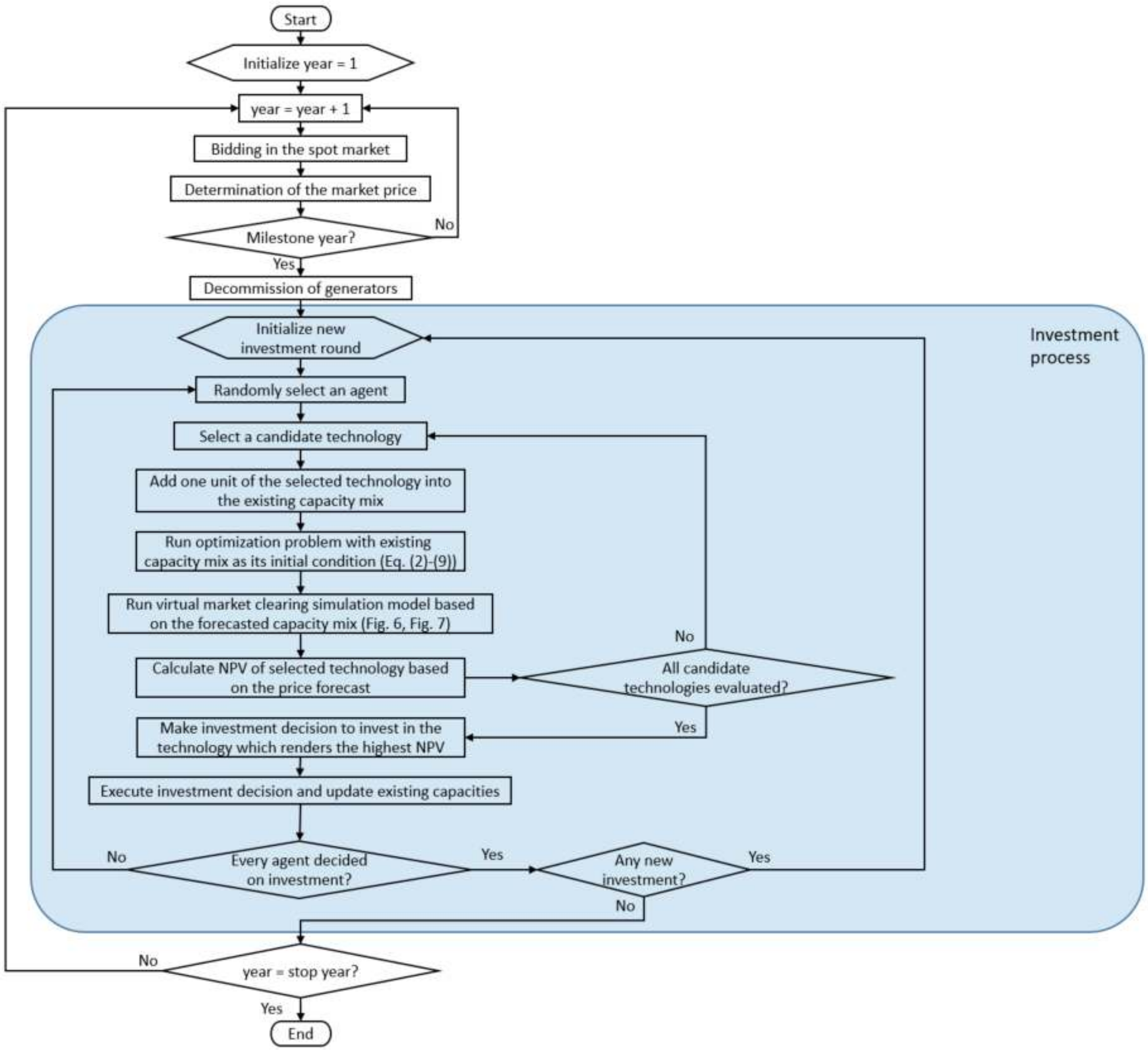
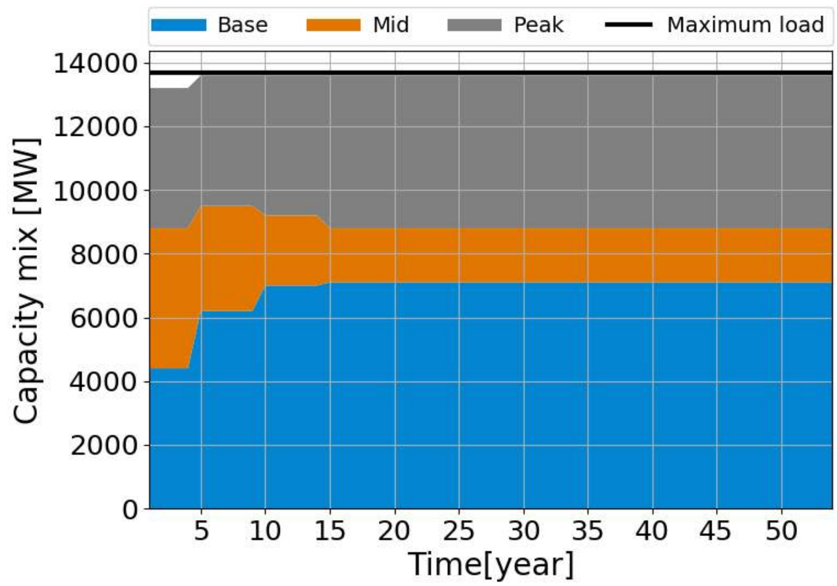
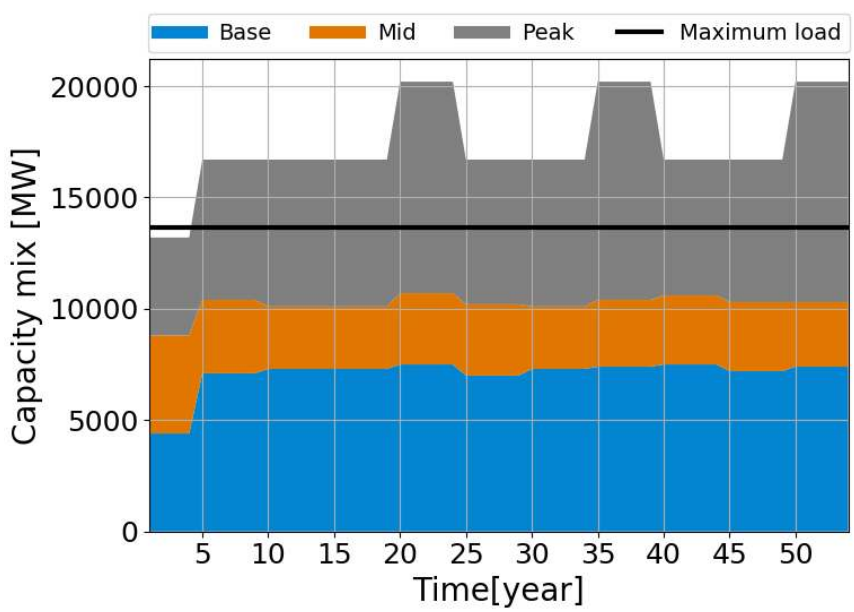


Fig. A2. Overview of the agent-based model with the novel price projection method embedded into investment processes.

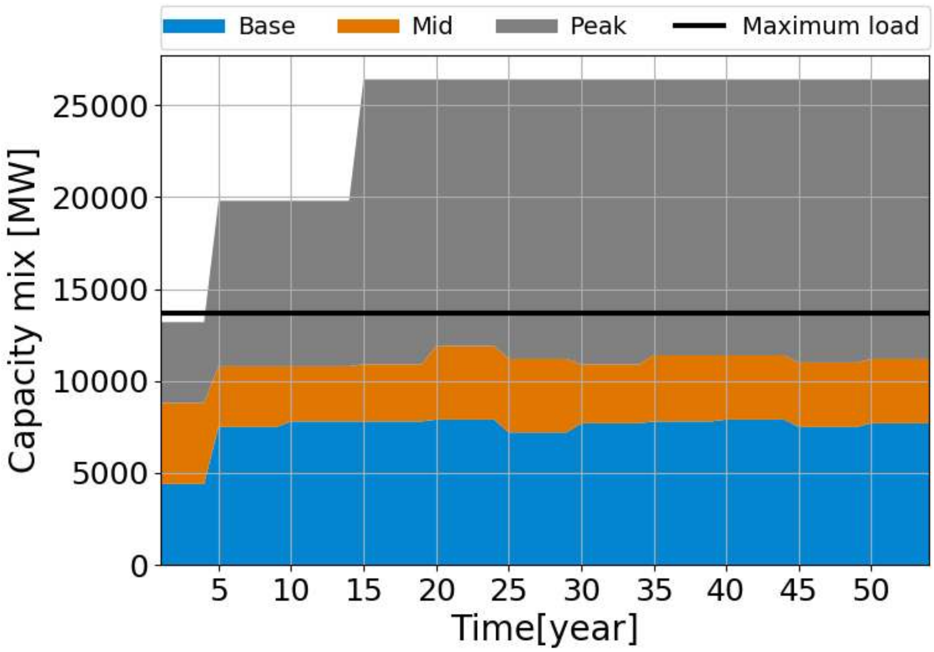
Appendix III. The pathway to equilibrium (of the cases shown in Fig. 8)



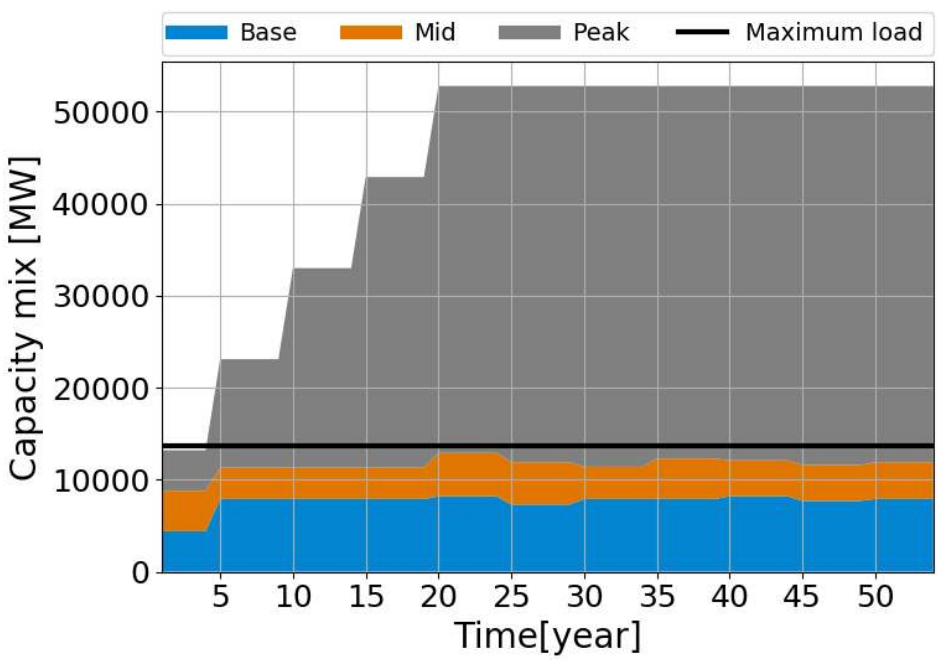
(a) The pathway to the equilibrium of the simulation results with "*myopic agent*" price projection method, the parameter look-ahead horizon is 5 years.



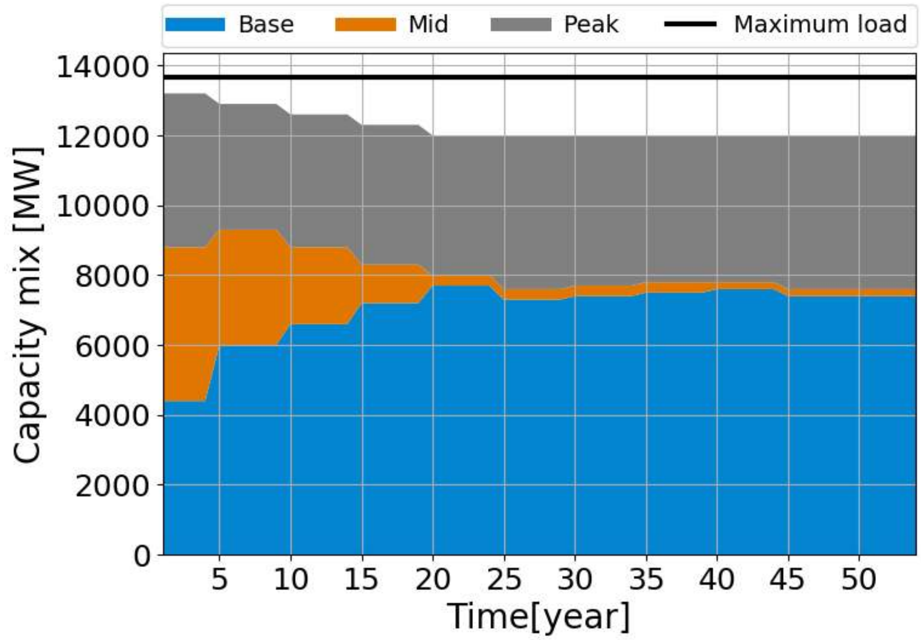
(b) The pathway to the equilibrium of the simulation results with "*myopic agent*" price projection method, the parameter look-ahead horizon is 10 years.



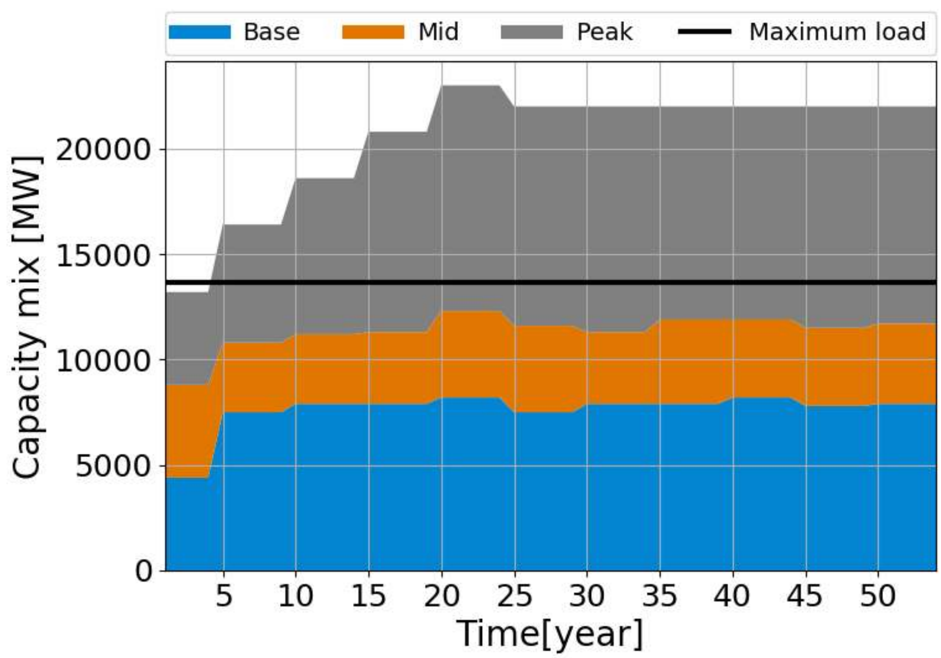
(c) The pathway to the equilibrium of the simulation results with "*myopic agent*" price projection method, the parameter look-ahead horizon is 15 years.



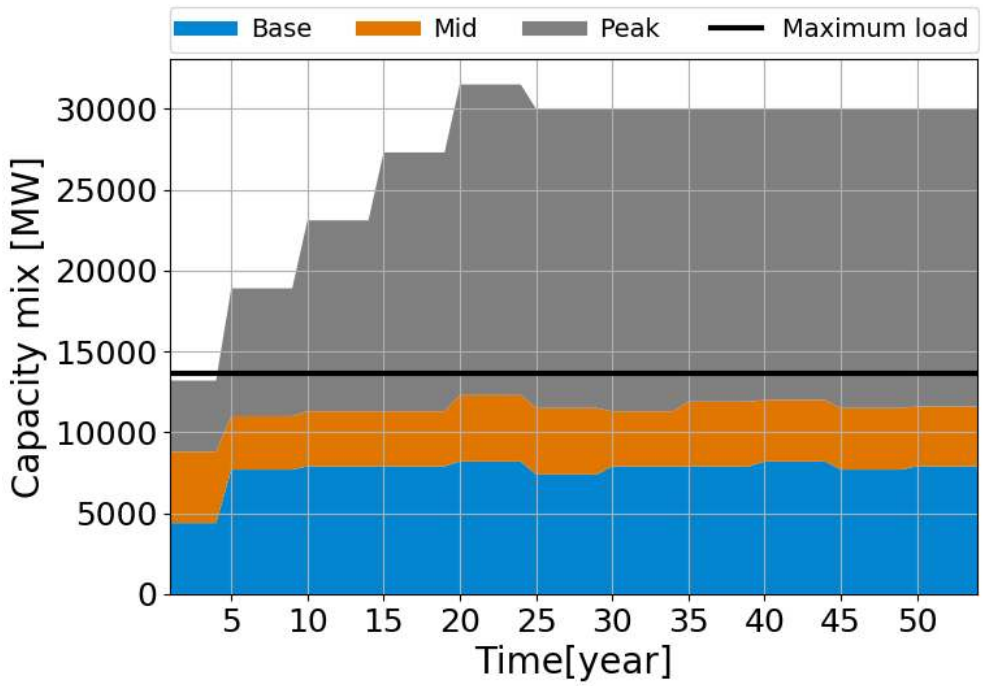
(d) The pathway to the equilibrium of the simulation results with "*myopic agent*" price projection method, the parameter look-ahead horizon is 20 years.



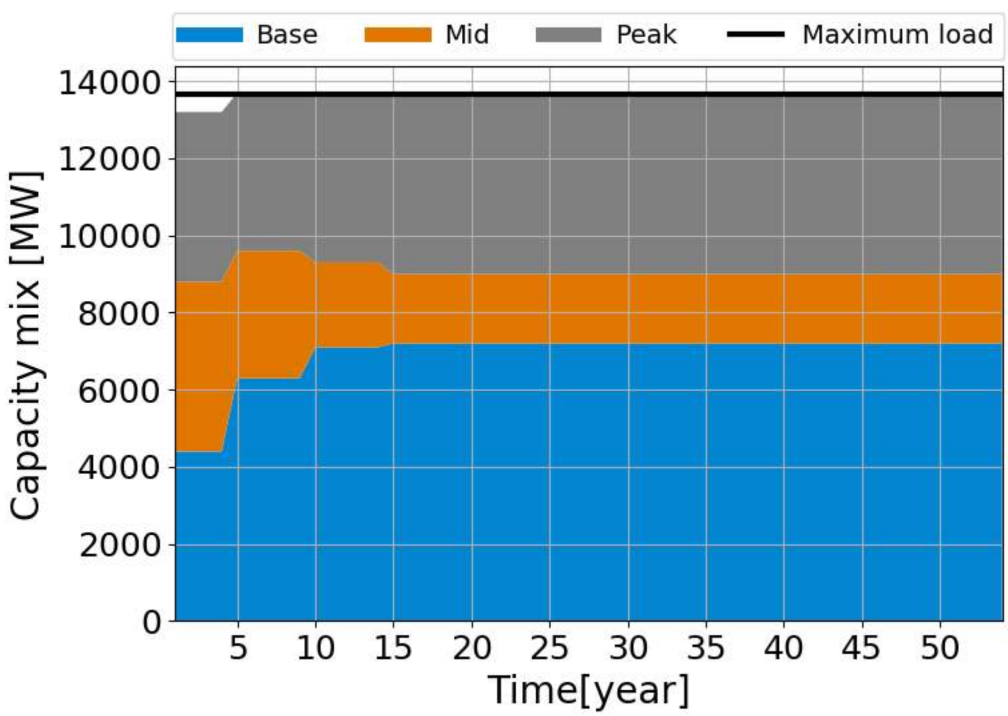
(e) The pathway to the equilibrium of the simulation results with "*exogenous scenarios for future investments*" price projection method, the values of the scenario tree is Case (a) as shown in Table 4.



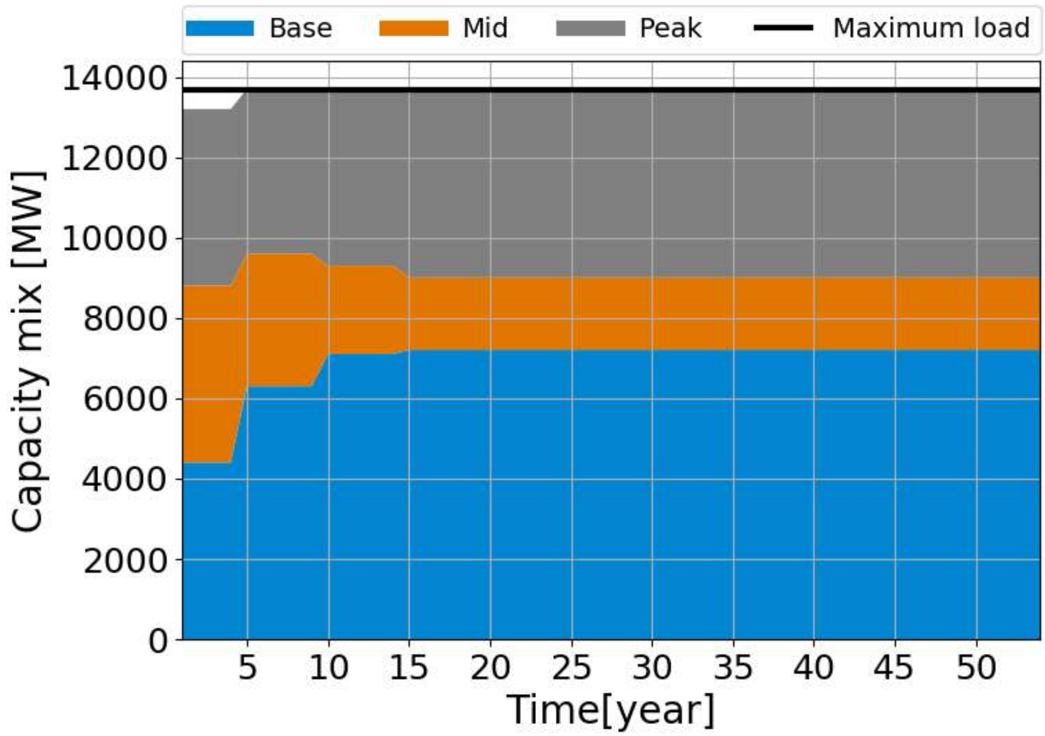
(f) The pathway to the equilibrium of the simulation results with "*exogenous scenarios for future investments*" price projection method, the values of the scenario tree is Case (e) as shown in Table 4.



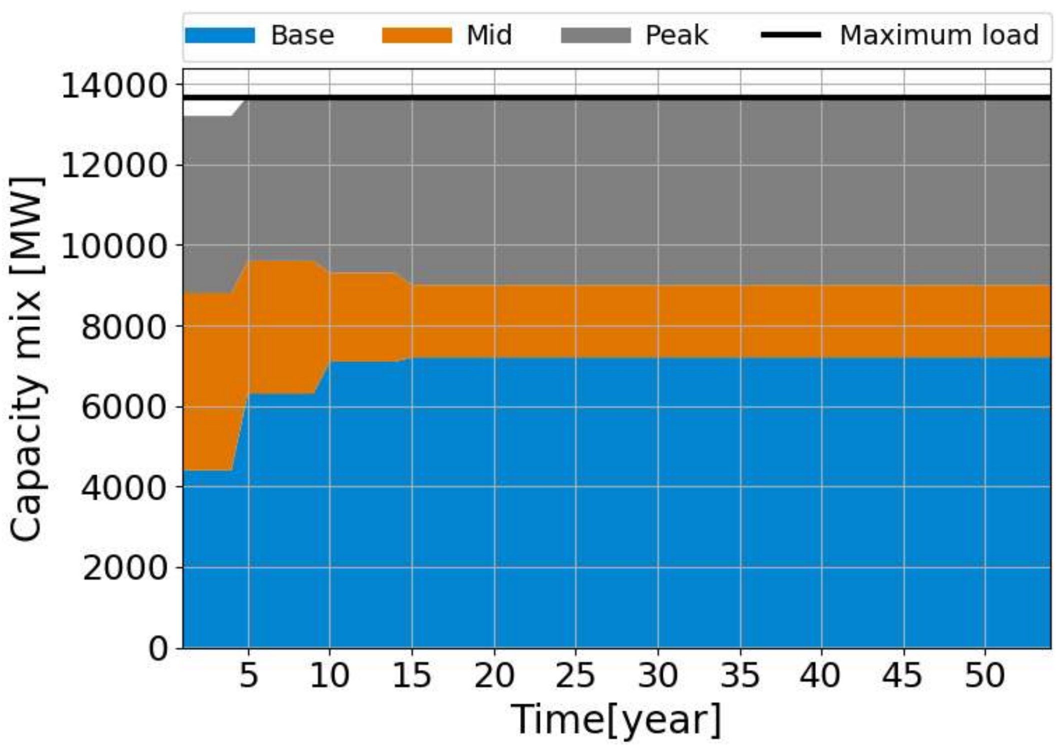
(g) The pathway to the equilibrium of the simulation results with "*exogenous scenarios for future investments*" price projection method, the values of the scenario tree is Case (i) as shown in Table 4.



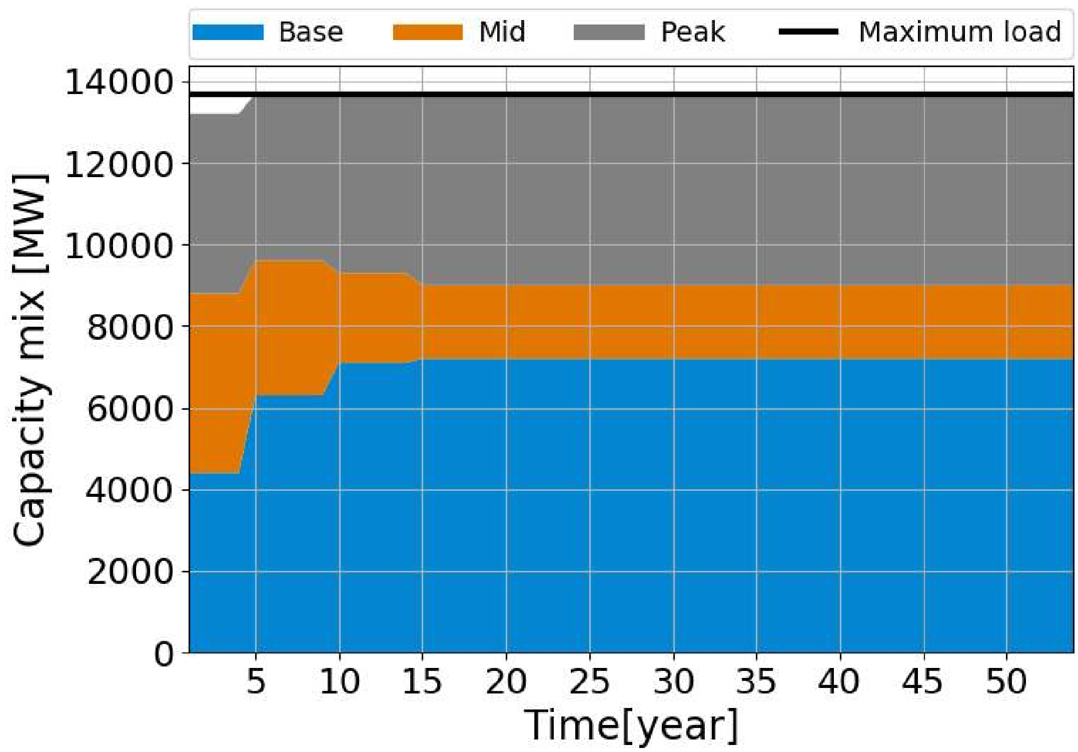
(h) The pathway to the equilibrium of the simulation results with "*cost-minimizing future investments*" price projection method, the parameter look-ahead horizon is 5 years.



(i) The pathway to the equilibrium of the simulation results with "*cost-minimizing future investments*" price projection method, the parameter look-ahead horizon is 10 years.



(j) The pathway to the equilibrium of the simulation results with "*cost-minimizing future investments*" price projection method, the parameter look-ahead horizon is 15 years.



(k) The pathway to the equilibrium of the simulation results with "*cost-minimizing future investments"* price projection method, the parameter look-ahead horizon is 20 years.

Fig. A3. The pathway to equilibrium (of the cases shown in Fig. 8).

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On the research group:

The **Energy Systems Integration & Modeling Group** is part of the division of Applied Mechanics and Energy Conversion (TME) of the Department of Mechanical Engineering of KU Leuven in Belgium. E. Delarue and W. D'haeseleer lead this research group, currently about 15 PhD students and post-doctoral research fellows, dedicated to the modeling of integrated energy systems and markets. This young research group has already gained significant expertise and international recognition in the field. A major strength of this group is its interdisciplinary focus (techno-economic models, link to energy policies and markets). The group is further strongly embedded in EnergyVille, an association of the Flemish research institutes KU Leuven, VITO, imec and UHasselt in the field of sustainable energy and intelligent energy systems. EnergyVille brings research, development, training and industrial innovation together under one name, in close cooperation with local, regional and international partners.