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Can an energy only market enable resource adequacy in a decarbonized power system? A co-simulation with two agent-based-models

I. Sanchez Jimenez [a,*], D. Ribó-Pérez [b,a], M. Cvetkovic [c], J. Kochems [d], C. Schimeczek [d], L.J. de Vries [a]

[a] Delft University of Technology, Faculty of Technology, Policy, and Management, Delft, 2600 GA, The Netherlands
[b] Institute for Energy Engineering, Universitat Politècnica de València, Valencia 46022, Spain
[c] Delft University of Technology, Faculty of Electrical Engineering, Mathematics and Computer Science, Delft, 2628 CD, The Netherlands
[d] German Aerospace Center (DLR), Institute of Networked Energy Systems, Curiestr. 4, 70563 Stuttgart, Germany

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ABSTRACT

Future power systems, in which generation will come almost entirely from variable Renewable Energy Sources (vRES), will be characterized by weather-driven supply and flexible demand. In a simulation of the future Dutch power system, we analyze whether there are sufficient incentives for market-driven investors to provide a sufficient level of security of supply, considering the profit-seeking and myopic behavior of investors. We co-simulate two agent-based models (ABM), one for generation expansion and one for the operational time scale. The results suggest that in a system with a high share of vRES and flexibility, prices will be set predominantly by the demand's willingness to pay, particularly by the opportunity cost of flexible hydrogen electrolyzers. The demand for electric heating could double the price of electricity in winter, compared to summer, and in years with low vRES could cause shortages. Simulations with stochastic weather profiles increase the year-to-year variability of cost recovery by more than threefold and the year-to-year price variability by more than tenfold compared to a scenario with no weather uncertainty. Dispatchable technologies have the most volatile annual returns due to high scarcity rents during years of low vRES production and diminished returns during years with high vRES production. We conclude that in a highly renewable EOM, investors would not have sufficient incentives to ensure the reliability of the system. If they invested in such a way to ensure that demand could be met in a year with the lowest vRES yield, they would not recover their fixed costs in the majority of years.

1. Introduction

Early investment theory in power systems argued that spot pricing could lead to optimal investment incentives and decisions [1]. However, subsequent research has emphasized that the ideal conditions of perfectly competitive markets, including perfect information, absence of market distortions, risk aversion, and market power, do not exist in the power sector [2–5]. Several studies have suggested that the current market design may not deliver the required investments to ensure a transition to a future carbon-free power system [6–8]. In this study, we seek to determine to what extent an Energy only Market (EoM) can be expected to provide enough investment incentives for the market to reach system adequacy. Specifically, we analyze investments in an EoM and the propensity of this market design to guarantee cost recovery for all relevant technologies. We use an Agent-Based Model (ABM) to simulate myopic investment behavior and to evaluate the effects of weather year variability on the long-term performance of an EoM.

Future systems will rely on vRES and will require more demand-side flexibility than current ones to integrate them. Due to the variability of vRES, supply-side uncertainty increases. Recent studies have shown that in a market dominated by resources with near-to-zero marginal costs, the electricity price will be mostly set by carbon-free dispatchable backup generators, storage, and demand response [9,10]. One of the main policy challenges for electricity markets is to design market rules that allocate resources efficiently and ensure the security of supply while minimizing costs. Analyzing a model of a future system can help policymakers make early adjustments to the market design, thereby reducing regulatory uncertainty for investors. Most studies of future systems are based on optimization models [11], which assume perfect competition, resulting in an equilibrium mix with the lowest system costs. However, prior research has shown that historically, actual generation expansion has not followed cost-optimal projections. For instance, [12] calculated a 9 to 23% discrepancy between optimal

* Corresponding author.
E-mail address: I.J.SanchezJimenez@tudelft.nl (I.S. Jimenez).

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Nomenclature

Abbreviations

ABM	Agent-based model
$AMIRIS$	**A**gent-based **M**arket Model for the **I**nvestigation of **R**enewable and **I**ntegrated Energy **S**ystems
B	Baseline scenario
CFD	Contracts for Difference
CF	Capacity factor
CRM	Capacity Remuneration Mechanism
COV	Coefficient of Variance
EH	Energy yield High scenario
EL	Energy yield Low scenario
EM	Energy yield Median scenario
$EMLab$	**E**nergy **M**odelling **Lab**oratory
ENS	Energy Not Served
EoM	Energy only Market
FLH	Full load hours
GA	Global ambition
IRR	Internal Rate of Return
KPI	Key Performance Indicator
$LESM$	Long-term Energy System Models
$LOLE$	Loss Of Load Expectation
LS	Load Shedding
ID	Increased Demand scenario
NPV	Net Present Value
SP	Stochastic Profiles scenario
$UCED$	Unit Commitment and Economic Dispatch
$VoLL$	Value of Lost Load
$vRES$	variable Renewable Energy Sources
$WAVG$	Weighted average
WTP	Willingness To Pay

Parameters

A	Annuity
$CAPEX$	Capital Cost
FC	Fixed cost
CF	Capacity Factor
DP	Downpayment
DR	Debt ratio
ER	Equity ratio
i	Interest rate
Rev	Revenues
ρ	equity interest rate
$WACC$	Weighted Average Cost of Capital
T_C	Construction time
T_{EL}	Expected Lifetime
VC	Variable cost
$VoLL$	Value of Lost Load

projections and actual generation expansion. Optimization models can incorporate multiple technical constraints and consider uncertainties to find an optimal solution. In contrast, alternative methods such as ABMs offer the possibility of investigating the impact of policies, considering limited information and strategic decision making. In general, generation expansion models do not intend to predict future capacity, but to give insights on factors that would impact the energy systems.

One of the reasons for the disparity between optimal solutions and real markets is that investors make investments according to expected revenues rather than making system cost-minimal decisions [13]. Moreover, lumpy investments and long lead times prevent the market from reaching an equilibrium [14]. Furthermore, investors may face uncertainty regarding competitors' decisions and future plans, commodity prices, technology costs, among others. As Tesfatsion [15] explains, actors in liberalized markets trade with imperfect information, limited foresight, and bounded rationality. Capacity expansion Agent-Based Models (ABMs) can mimic profit-seeking energy producers with myopic behavior and bounded rationality. Similarly, operational ABMs allow scheduling resources with a rolling time horizon, incomplete information, and no equilibrium. In our research, we simulate both investment and operational decisions with ABMs that allow us to analyze an energy system that is not necessarily in a long-run equilibrium.

We analyze a future electricity system, based in the Netherlands, with a co-simulation of AMIRIS [16] and EMLabpy, which is derived from EMLab [17]. EMLabpy is a long-term ABM that simulates the investment decisions of energy producers, while AMIRIS is a short-term ABM that simulates dispatch. EMLab, as a standalone model, cannot represent multiple types of flexibility, while AMIRIS does not have an investment algorithm. Hence, this co-simulation allows us to use the strengths of both models. To reflect the flexibility of the future system as much as necessary, we execute the model on an hourly basis, considering the flexibility of demand and weather-dependent vRES. While there have been some investment and dispatch studies with the ABM model PowerACE for Germany [18], this is the first study that takes into account operational and investment decisions with bounded rationality and that integrates multiple flexibility options (battery storage, load shedding, and hydrogen electrolyzers), as well as model-endogenous decommissioning. To the best of our knowledge, this is also the first co-simulation of ABMs where the investment decisions are determined in an iterative process with a dispatch ABM.

Future uncertainties that will arise from weather patterns and their correlation with demand, as well as their impact on power prices and system adequacy, are not yet well understood. To evaluate the performance of an EoM under weather variability, multiple sequences of 40 random weather years are tested. Besides the commonly used reliability indicators, such as loss of load and energy not supplied, we analyze the volatility of electricity prices and market-based cost recovery, since these may also be early indicators of resource inadequacy [9]. We demonstrated that EoM will not be sufficient to ensure the security of supply in future 100% vRES systems and recommend exploring options for capacity remuneration mechanisms.

The rest of the research is organized as follows. Section 2 discusses the current literature around investment theory in the power system, agent-based models, and model coupling. Section 3 presents the relevant details of EMlabpy and AMIRIS and describes how these are applied in a co-simulation. Section 4 enlarges upon the used data and presents the case study. Section 5 shows the results from the analysis and their implications. Finally, Section 6 concludes by summarizing the paper's main findings.

2. Literature review

2.1. Investment theory in power systems

According to the peak load pricing theory, in the long run, generators should recover their costs from scarcity rents [2]. A major impediment to the completeness of an electricity market, as described by Caramanis, Bohn, and Schweppe [1], has been the lack of fully flexible demand, which prevents the true Value of Lost Load (VoLL) during scarcity from being reflected in the market. Furthermore, regulatory price caps can enhance the missing money problem [3], which refers to insufficient revenues to cover the costs incurred by the generators. Market interventions, such as the introduction of caps on infra-marginal rents in response to the European energy crisis, and low participation in long-term markets have hampered a theory ideal market-led investment system [8]. Even if there were enough incentives, market participants might not perceive them. This is known as the missing market problem. Newbery explains that an EoM could work if the sources of the missing money and the missing market were removed [19].

In contrast to the theory of optimal investments, market failures that prevent an investment equilibrium are caused by a lack of risk allocation mechanisms, lumpy investments, long lead times, imperfect information, regulatory uncertainty, and uncertain interconnections, among others [14,20]. All of these sources of myopic decision-making lead to a preference for low capital cost projects and prioritizing short-term profits over long-term projects as this can cause investment cycles and threaten the system's security of supply [17,21–25]. Under-investment could result in large profits for generators [6] at the cost of society. Therefore, ensuring system adequacy, i.e. sufficient installed capacity to meet demand, can also prevent large money transfers that occur when prices are exceptionally high for an extended period of time [14], such as the situation that occurred in ERCOT during the 2021 Uri storm [26].

With the increase of technologies with marginal costs close to zero, base load technologies have suffered from reduced capacity factors. It is an open question if a decarbonized system could enable investors to recover their investments. Lately, several authors have recognized that as power systems shift from low capital costs and high operational costs to systems with low operational costs and high capital costs, capacity remuneration mechanisms might become more necessary [27]. In addition, the volatility of electricity prices from late 2021 to 2023 has reinforced the inclination towards capacity remuneration mechanisms that can ensure the security of supply [28]. In a future market with volatile supply and flexible demand, as opposed to today's market with volatile demand and flexible supply, capacity mechanisms can engage the flexible demand to fulfill an important pillar of market design, which is affordability. Flexibility, which is defined as the ability to adjust supply and demand in response to changing conditions, will become a critical factor in enabling a decarbonized electricity market [6,28].

2.2. Weather uncertainty

Around 2015, many gas plants in Europe were mothballed or prematurely closed as they were used less than planned. Besides carbon prices and fuel prices, a major cause was a lower demand than anticipated [29]. In a future electricity system, the weather will be a major source of uncertainty. vRES outputs can be very volatile, especially wind generation [30], leading to years with considerably larger vRES generation than others. Collins et al. [31] analyzed the impact of inter-annual weather variability in a Europe-wide optimization study and found the total generation costs variability would increase fivefold, from 2015 to 2050. Zeyringer et al. [32] compared investment decisions based on a single weather year against investment decisions by considering a ten-year horizon of different weather years. They found that optimizing for the longer time period increased the required installed capacity of flexible generators and total system costs compared to optimizing for each weather year individually; however, optimizing for individual weather years led to operational inadequacy and missing decarbonization goals. Price et al. [33] also analyzed how considering weather variability can result in distinct spatial deployment patterns.

Under an EoM, years characterized by high production will likely lead to lower electricity prices. If no hedging opportunities exist, investors may under-invest due to this uncertainty. This can aggravate one of the most important difficulties, coping with extreme weather periods when both wind and solar power generation are low or almost non-existent, a phenomenon also known as Dunkelflaute [34].

Regarding short-term uncertainty, vRES-dominated markets might exhibit high price volatility correlated to the availability of renewable generation. The addition of generation capacities of specific technologies can hamper their own business case due to the generation autocorrelation and price depression [35]. However, demand flexibility might overcome this problem by becoming the price-setting instance in contrast to the current system where prices are determined by generators' marginal costs, thus, improving the business case for vRES generators [36].

2.3. Simulating investment decisions with ABMs in electricity systems

Agent-Based Models (ABM) follow a bottom-up approach to modeling complex systems that involves simulating the behavior of individual actors (agents), such as generators, consumers, and other market participants, as well as modeling their interactions. ABM allows for the exploration of emergent phenomena that result from the interactions between agents and the study of the effects of environmental or individual agent behavior changes. ABMs have been used to study a wide range of electricity market design issues. By simulating agents with limited information, ABM allows studying generators with strategic behavior, their strategies participating in different markets as well as imperfect information in consumers' participation. Operational ABMs that solve Unit Commitment and Economic Dispatch (UCED) have been applied to study the impact of a high share of renewable energy and associated policies. For instance, Frey et al. [37] analyzed the risk of downward price dynamics in the German market premium scheme if vRES went from price takers to price setters.

Capacity expansion models, also known as Generation Expansion Planning Models (GEPM), that use optimization techniques often mimic a benevolent monopolistic system planner taking all decisions. Or, seen from the energy producers' perspective, in these types of models, market participants have perfect information about other agents' decisions, hence enabling a long-run market equilibrium (assuming perfect competition), where cost recovery is guaranteed.[1] This assumption is less realistic during an energy transition with an evolving capacity mix. Furthermore, optimization models usually incorporate a constraint for the supply to meet the demand and assign a high penalty for not covering all demand. In contrast, ABMs allow simulating myopic decisions where agents maximize their profits and no equilibrium is guaranteed [38], thus allowing insufficient generation adequacy and counteracting policies to be simulated. Furthermore, ABMs allow incorporating agents' behavior and market rules, for instance in the commissioning and decommissioning of power plants.

Previous investment ABMs have focused on questions regarding firms' heterogeneity, risk aversion, prospect theory in investment behavior [39], investment preferences [40], capacity mechanisms [41,42] and the cross-border effects of these mechanisms [43] as well as the effect of CO_2 policies [5,44]. More recent studies have included flexibility agents, e.g. [45] considers hydrogen in an ABM with an optimization model for the dispatch, while [46] investigates the impact of battery expansion from prosumers. In [25], Anwar et al. present a detailed comparison of the latest generation expansion ABM models.

Limitations of AMBs are that emergent behavior may be difficult to interpret, and results may be sensitive to the choice of a specific agent strategy representation. Another limitation is the model complexity.

Oftentimes, energy system models use different methods to reduce the time series data and keep computational times feasible. Some options are to downsample data, cluster data, take representative hours/weeks by heuristics, or construct synthetic data [47]. Most studies on generation consider only one weather year, some studies make stochastic evaluations (i.e. [48]), and fewer studies consider

[1] Mixed complementarity problems allow simulating profit-maximizing agents with imperfect information but assume an equilibrium

investments based on an hourly time series analysis. Newer methods consider operational uncertainty with multi-horizon stochastic programming but still rely on representative days for investment decisions (i.e. [49]). Aggregating data can underestimate extreme values and loose chronology, which is relevant for adequacy analysis. Several studies have shown that reducing the scale to some hours or weeks per year results in inaccurate results and tends to underestimate the flexibility requirements [50]. Hoffmann et al. [51] present a summary of models that have aggregated data. They explain that grouping with a too low number of segments or typical days can introduce a systematic bias and propose an algorithm that finds a trade-off between these variables. Moreover, Helistö et al. [50] found that the impact of simplifying operational details is less than that of simplifying temporal representation, especially while modeling power systems with a large volume of flexible capacity. Flexibility will be a key enabler of a decarbonized power system, and thus it will be more relevant to consider hourly operational decisions to value storage and flexibility accurately. Therefore, it is relevant to base investment decisions considering a high temporal resolution. From the reviewed investment ABMs, only PowerACE makes an hourly analysis for investment decisions. To avoid losing accuracy, we also apply hourly modeling resolution in this study.

2.4. Co-simulation

Energy system simulations are becoming increasingly complex, needing higher temporal and spatial resolution, better uncertainty representation, and incorporating policy and human behavior [52]. Instead of expanding the scope of each model, co-simulation offers the possibility of exploiting the strengths of existing models and integrating exogenous information from other models to keep the computational complexity low. In a co-simulation, the independent simulators exchange their inputs and outputs for a given time step, and based on the received information each simulator progresses to the next step [53].

Soft-linking, on the other hand, involves utilizing the output of one model as the input of another model, but not necessarily in real-time. Soft-linking may be either unidirectional or bidirectional [50]. Most unidirectional soft-linkings have been performed to assess the operation of previously determined investment results and to incorporate the technical details into models with a broader scope [54]. Some studies have used unidirectional soft-linking to integrate spatially and temporally high-resolution results, [32] optimized the location of technologies with a power model from a less granular GEPM.

In bi-directional soft-linking, the UCED model results are iteratively used to update parameters or add constraints to the GEPM [55]. For example, [56] soft-link the investment optimization model (TIMES) with an operational probabilistic model to reevaluate the capacity credits from different technologies and to reassess the security of supply of the future French power system. To the best of our knowledge, there has not been a study where the investment decisions are based iteratively on detailed dispatch results from another ABM.

Co-simulations can be facilitated by the use of workflow management tools. One of them is the Spinetoolbox [57]. Spinetoolbox is a graphical workflow management application that enables the coupling of energy models with distinct scopes and spatio-temporal resolutions. The tool manages the data flow between modules and the creation and visualization of workflows. Several studies have already used the Spinetoolbox to couple energy models. Among them, [58] formulates joint day-ahead energy and balancing capacity markets clearing, and [59] explores the interaction between long-term storage deployment and the expansion of the transmission capacity.

3. Methodology

3.1. Co-simulation of EMLabpy and AMIRIS

In this publication, we study the suitability of an EoM in a decarbonized renewable energy system by co-simulating two ABMs. In the co-simulation, investment decisions are made by an ABM, EMLabpy, based on the dispatch results from another ABM for the short-term market, AMIRIS. In this way, myopic agent behavior with limited information can be simulated on the operational time scale as well as for investment decisions. AMIRIS (Agent-based Market model for the Investigation of Renewable and Integrated energy Systems) captures the bidding of agents in the day-ahead market, whereas EMLabpy simulates the myopic investment decision-making process.

AMIRIS – developed by the German Aerospace Center (DLR) [16] – allows to simulate business-oriented bidding whereby policy incentives, e.g., for vRES support might be incorporated. In our study, AMIRIS is applied with a rolling weekly dispatch scheduling of flexible agents (see 3.2.4). EMLab (Electricity Modelling Laboratory) is a model that enables the investigation of policies on generation expansion and other policies [17]. In EMLab, investment decisions are based on the expected returns from a simplified dispatch algorithm with a segmented load duration curve. Although it can model storage, the demand is aggregated into a segmented load curve with a limited representation of flexibility [60]. In contrast, AMIRIS offers the representation of several flexible technologies, such as electricity storage, electrolyzers, or heat pumps. Hence, through co-simulating we combined the strengths of both models.

EMLab was originally developed as a standalone model in Java. In order to facilitate the integration with AMIRIS, EMLabpy, which was inspired by EMLab, was developed modularly in Python. In contrast to the original version of EMLab, no segmented load duration curve is used anymore, but rather detailed dispatch results from AMIRIS are the basis for evaluating investment decisions. We execute the co-simulation of EMLabpy and AMIRIS using the Spinetoolbox.[2]

3.2. Workflow overview

Fig. 1 depicts an overview of the employed workflow. Fig. 14 in the appendix shows the workflow setup in Spinetoolbox. Each module is explained in detail in the following subsections.

Each simulation year commences with the decommissioning of power plants. Then, the data is prepared to be read by AMIRIS. AMIRIS then clears the market on an hourly basis. After this, the financial performance of all power plants is calculated and saved. Subsequently, investment decisions in EMLabpy are made based on AMIRIS' market results for a future year. A data preparation step exports the data for AMIRIS to clear the market four years ahead (these will be referred to as look-ahead years) of the simulation year currently evaluated. Previous to the yearly cycle, an initialization investment loop is executed to account for the investment decisions made in years prior to the simulation's beginning year.

Spinetoolbox allows to manage multiple databases to store different input and output data. In this workflow, the EMLabpy-database stores the data to run all modules, while the AMIRIS database stores the yearly dispatch and market results. The market results are used in the financial-results module (see in appendix 15 the data workflow).

3.2.1. Initialization investment loop (in EMLabpy)

We solve a brownfield problem. If there is insufficient generation capacity at the start of a simulation, severe shortages may occur in the first simulated years. For this reason, an initialization investment loop is executed to account for investment decisions made before the simulation.

3.2.2. Decommission (in EMLabpy)

Power plants are decommissioned after their technical lifetime is reached. This approach allows the investor-agent to have a precise estimate of the total operational capacity.

[2] The code can be accessed at: https://github.com/TradeRES/toolbox-amiris-emlab.

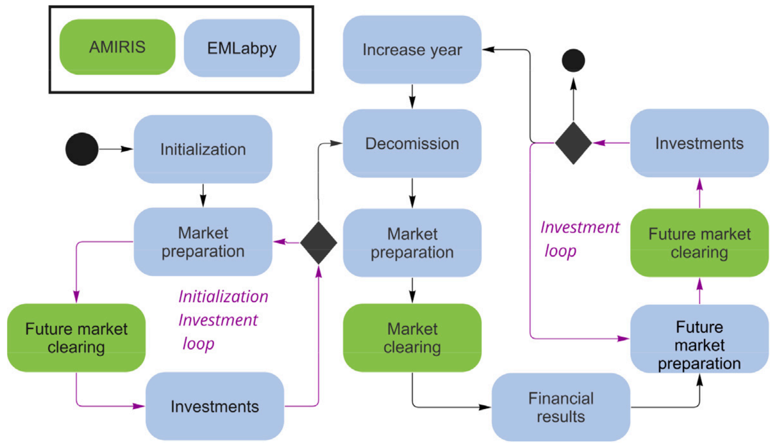


Fig. 1. Overview of the co-simulation methodology.

3.2.3. Market preparation (in EMLabpy)

The market preparation module exports data from the workflow database and prepares them for the simulation in AMIRIS. Power plants that should be operational during the simulation year are scheduled. Each power plant's capacity, efficiency, and operational costs as well as overarching parameters, such as fuel prices, demand profiles with their respective Willingness To Pay (WTP), and vRES profiles are transferred to AMIRIS inputs.

This module is also executed to simulate the future market for the investment module 3.2.6. For the future-market preparation step, the data for 4 years ahead is compiled. All power plants that should be operational at the time are considered, in that way the energy producer agent is aware of all investments made up until the current investment iteration. In addition, potential technologies are added to the list of future power plants.

3.2.4. Market dispatch (in AMIRIS)

AMIRIS simulates one year of dispatch in hourly resolution using the input data provided by EMLabpy. Three distinct categories of flexibility sources of AMIRIS are utilized, namely price-based load shedding, energy storage, and a generic load shifting agent that is operating with a given opportunity cost-based price cap.

Load-shedding agents are represented by demand profiles and their maximum VoLL, which is their WTP for electricity. During periods of scarcity, loads are curtailed in increasing order of WTPs until the market is cleared. The scheduling decisions of storage agents are based on an initial forecast which is calculated by intersecting the bids of all supply-side agents (conventional and vRES as well as fixed storage discharging) with the inflexible demand-side agents' bids. The storage agent bids are based on the median forecasted electricity price plus a margin in case of discharging and minus a margin in case of charging. The margin acts as a buffer for charging and discharging losses.

Although this strategy is robust for representing simultaneously competing agents, these agents are unaware of the bids of other flexible agents. Thus, the strategy yields suboptimal results with respect to the dispatch and agent profitability. More research is required to address this algorithmic shortcoming. The storage dispatch schedule is planned for a rolling time horizon of one week. As the price can be affected by its own bids, as well as other flexible agents' bids, if the intended storage dispatch schedule cannot be met, i.e. the storage bids cannot be fulfilled due to price deviations, the storage trader calculates a new schedule in the subsequent hour to account for the differing state of charge of the storage unit.

The generic load-shifting agent is represented by three parameters: an opportunity cost-based price cap, a monthly flexible demand, and a maximum accepted price. In each forecasting period, the agent chooses the lowest price hours to cover the demand which is assumed to be fully flexible within that given planning period. The additional load added by this agent may increase the price. Therefore, in the scheduling process, price changes due to its own dispatch are taken into account. If some demand cannot be fulfilled in the current scheduling window, demand might be shed at first, but this unfulfilled demand is transferred to the subsequent rolling planning window to be fulfilled at a later time.

3.2.5. Financial results (in EMLabpy)

Following the market clearing, loans and down payments are registered. The equity payments are paid during the construction time (after the permit time is concluded). The loans are paid during the lifetime of the power plants starting from the commissioning year. Each power plant's spot market revenues, production, total costs, Internal Rate of Return (IRR), and Net Present Value (NPV) are saved in a database. The yearly costs (fixed costs, variable costs, loans, and down payments) and revenues are totaled and stored for each single energy producer.

3.2.6. Investment decisions (in EMLabpy)

Investment decisions are based on the investors' future expectations which are derived from the AMIRIS future market outcomes and the technical and financial conditions, as shown in Fig. 2. First, EMLabpy evaluates the physical limitations of each technology. If the capacity limits per technology, as specified in 12, have not been exceeded, the NPV is computed for each technology as shown in algorithm 1, and the technology with the highest positive profitability expectation is chosen for investment (see Fig. 2).

In EMLabpy, generators' commissioning is scheduled for the same year for which future market expectations are calculated. However, as investments are made iteratively no equilibrium is guaranteed. Investment decisions take into consideration previous investments but do not account for subsequent investments; consequently, their profitability may be lower than anticipated. Following each investment decision, the future market is reevaluated in AMIRIS taking into account the new investments.

To reduce run time, 1 MW of each investable technology is evaluated on the future market. If the result of this 1 MW is positive, larger capacities are installed after a technology is chosen, as specified in the Table 11. To prevent overinvestments, as the NPV of the evaluated technologies approaches zero, the tested capacity is increased for subsequent investment iterations.

Algorithm 1 Investment algorithm

```
function < CALCULATE NPV>
    ER = (1 - DR)
    Debt = DR * CAPEX
    DP = (CAPEX * ER) / T_C
    Calculate A, using (1)
    for year ∈ {0 … T_C + T_EL} do
        if then year < T_C
            CashFlow[year] = −DP
        else
            CashFlow[year] = Rev − FC − VC − A
        end if
    end for
    calculate NPV using (2)
end function
```

[3]

$$A = \frac{Debt}{\frac{1}{i}(1 - \frac{1}{(1+i)^{T_{\mathrm{EL}}}})} \tag{1}$$

$$NPV = \sum \frac{CashFlow_t}{(1+\rho)^t} \tag{2}$$

3.3. Model verification of the investment algorithm

The EMLabpy investment module was validated by simulating an agent with perfect foresight and executing a scenario with fixed costs, weather profiles, and no technical constraints. We observed that all the technologies in which it was invested presented positive NPVs and investment cost recovery on average close to the input Weighted Average Cost of Capital (WACC) of 7%. This demonstrates that the investment algorithm performs as anticipated by investing in technologies and capacities until they are no longer profitable.

4. Experiment design: simulating a future decarbonized power system

Using the workflow described above, we simulate a decarbonized power system based in the Netherlands to investigate the dynamics of a future power system and analyze the impact of weather uncertainty on the market and its long-term implications. In this section, we describe the data and the scenarios.

4.1. Data

4.1.1. Future weather data

Technological advancements, such as the deployment of higher wind turbine hub heights, efficiency improvements, and longer blades are expected to increase the full load hours of wind and solar energy. Offshore wind farms have been and will continue to be placed further from the shore, being able to capture a higher wind speed spectrum. To scale the historical Capacity Factor (CF) time series, an algorithm is applied to increase the full load hours per technology to future expected capacity factors, according to IRENA [61] and IEA [62], see Table 12. The code for the augmentation of the profiles can be found in [63]. The historic weather profiles are taken from the Merra2 database.[4]

4.1.2. Load representation — weather-driven demand

We assume that household, commercial, and electric vehicle demands are triggered by consumer routines (weekdays), whereas heat pump demand is driven by the outdoor temperature. To determine the heating demand according to the weather and its correlation with vRES generation, we correlate the historical data for temperature with the hourly space heat requirements for the years (2008–2016) based on [65]. Due to the lack of data for the rest of the years (1980–2007 and 2017–2019), we perform a linear regression considering the hourly variations in heating demand. m_h and n_h are the slope and intercept calculated for every hour of the day. The regression for space heat demand is performed for temperatures under 18 °C. SHR_t represents the calculated space heat demand (MW) demand at time t and is always a non-negative value.

$$SHR_t = m_h \cdot T_t + n_h \tag{3}$$

We assume a fully electrified space heating demand with Air Source Heat Pumps (ASHP) and Ground Source Heat Pumps (GSHP). Their Coefficients Of Performance (COP) correlate with existing temperatures from the same database [65], but without considering hour-of-the-day differences. We considered ASHP and GSHP with radiators and excluded high temperatures to achieve the highest correlations. The correlation for ASHP is done with temperatures below 13 °C, while for GSHP below 15 °C.

$$COP_t^{GSHP} = m^{GSHP} \cdot T_t + n^{GSHP} \quad \forall COP^{GSHP} \quad \in 2.5 < COP^{GSHP} < 6.32 \tag{4}$$

$$COP_t^{ASHP} = m^{ASHP} \cdot T_t + n^{ASHP} \quad \forall COP^{ASHP} \quad \in 1 < COP^{ASHP} < 4.06 \tag{5}$$

Finally, we obtain the electricity consumption demand for space heating SHD_t by considering their hourly COP and the market shares (MS) of 0.6 for ASHP and 0.4 for GSHP, following [66] for households.

$$SHD_t = MS^{ASHP} \cdot SHR_t / COP_t^{ASHP} + MS^{GSHP} \cdot SHR_t / COP_t^{GSHP} \tag{6}$$

4.1.3. Flexible load representation — hydrogen, and industrial heating demand

While the focus of our research is on electricity market design, we make some assumptions about the composition of the future energy system. The production and storage of hydrogen are expected to provide an important function for periods with insufficient vRES. In Europe, hydrogen will be primarily used to decarbonize hard-to-abate sectors such as the industrial and transportation (e.g., maritime, aviation) sectors [67,68]; therefore, we assumed that electrolyzer operational costs and storage costs will be mainly borne by sectors other than the electricity sector. As a result, we do not simulate hydrogen storage investments or operations, as we only consider the production of green hydrogen and its use in the power sector.

The electricity demand to produce hydrogen is modeled as flexible (limited to the available electrolyzers' capacity). Hydrogen production is interrupted if the electricity price exceeds 33.4 €/MWh, which corresponds to the expected future market price of hydrogen (45 €/MWh [69]) times the efficiency of electrolysis (74%). Thus, hydrogen is produced when vRES production is sufficiently high and power prices are low. We simulated a completely flexible hydrogen production by simulating electrolysis as a load-shedding unit. As a simplification, we consider constant hydrogen prices under the assumption that in the future, there will be sufficient storage capacity and a well-established hydrogen market. In reality, prices will vary depending on several factors, including vRES generation, the diversification of hydrogen sources, the capacity and adaptability of electrolyzers, the availability of hydrogen transportation, imports, storage, and the interaction between the electricity and hydrogen markets.

[3] A = Annuity, CAPEX = Capital Cost, FC = Fixed cost, DP = Downpayment , DR = Debt ratio, ER = Equity ratio, i = Interest rate, Rev =Revenues, ρ = equity interest rate , T_C = Construction time , T_{EL} = Expected Lifetime , VC = Variable cost.

[4] www.renewables.ninja [30,64]

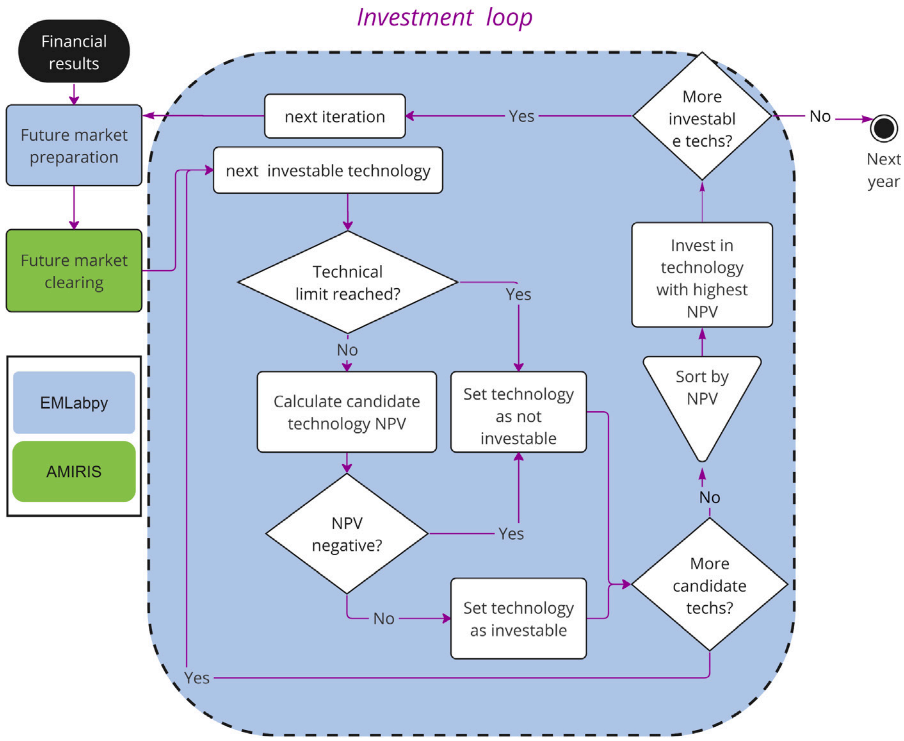


Fig. 2. The investment module can be located in the workflow overview 1.

Table 1
Summary of flexibilities in the model.

Load	Characteristics	Type of flexibility
Flexible consumer	Percentage of total load and grouped by VoLL	Load Shedder
Hydrogen	Constant demand, limited by electrolyzer capacity as well as prices	Load Shedder
Industrial heat	load-shifting unit with an opportunity cost-based price cap	Load Shifter
Heat pump	Yearly demand as a function of hourly temperature	Inflexible
EV	scaled up to EV share in 2050	Inflexible

We model industrial heating as a price-capped load-shifting agent (see Section 3.2.4). The yearly flexible industrial heating demand is extracted from COMPETES, which takes as an input ENTSO-E data [69]. If electricity prices are low, industrial demand is met with electric furnaces; otherwise, demand is shed or natural gas is used. Hence, the price cap for the industrial demand was 48.6 Euro/MWh.

For the rest of the demand, the ENTSO-E demand time series is scaled according to the 2050 global ambition scenario from the TYNDP [69] (6.1 TWh EVs and 144 TWh inflexible demand). Likewise, the electric vehicle profile load is based on 2015 but is scaled to 2050 to account for the projected fleet size. The EV profiles are modeled using the Charging Profiles of Electric Vehicles model (ChaProEV) [70], which uses electric vehicle parameters, user activities, and locations to generate charging profiles. The demand for heat pumps is included, as described in Section 4.1.2 (see Table 1).

4.1.4. *Load representation — load shedding*

Currently, AMIRIS has a limited capability of modeling competing load shifter strategies. To account for a high demand response, we model different load shedding clusters. Based on literature about load shedding in The Netherlands and Europe [71–73], we assume that 20% of the conventional demand has a lower VoLL than the market cap (4,000€/MWh). This sheddable demand includes EVs and heat pumps, but excludes industrial heating and electrolyzers demand. In summary, we model a highly flexible system in which 51% of the loads are sheddable (45% is the sheddable demand from electrolyzers and 6% has a lower VOLL than the market price cap), 13% of the loads are shiftable (from industrial heat), and only 35% are inflexible (see Table 2).

4.1.5. *Initial power plants*

The initial 2050 generation capacity mix of a stylized future Dutch system is extracted from the results of the optimization model COMPETES [72]. COMPETES is an optimization model used by the Dutch government in the country's Energy and Climate Plans [74]. The initial capacities and flexible resources resemble those planned in the Energy and Climate Plans. As nuclear technology costs are highly uncertain and its investments remain political, these tend to be centrally planned. For this reason, nuclear capacity is set constant according to COMPETES results. Similarly, the Electrolyzers capacity is also taken from COMPETES capacity of 41 GW, due to its better representation of sector coupling. From these initial capacities, we run the EMLabpy-AMIRIS workflow for 40 weather years with constant prices, temperature-dependent demand profiles, and capacity factor profiles (both will be referred to as weather profiles), achieving a stable capacity based on ABMs, which then we use as a base for the simulations.

The optimization and the ABM models resulted in different capacity mixes for several reasons. COMPETES makes a perfect foresight dispatch for a whole year, while within AMIRIS flexibility agents create weekly schedules. AMIRIS currently has a limitation for simulating the flexible operation of flexible sources simultaneously (see Section 3.2.4). The operation of combined heat and power plants, Power-to-H_2, gas-to-H_2, and H_2 storage as well as demand side response can be optimized within COMPETES, but not in AMIRIS. However, the largest difference

Table 2
Load flexibilities percentage from total demand.

Load	Type of flexibility	Type of load shedder	Load share	VOLL [€/MWh]
Conventional (residential, tertiary, transport, electrical appliances from industry, agriculture, others)	Sheddable	High LS	3.1%	1500
		Medium LS	1.55%	500
		Low LS	1.55%	250
	Inflexible		35.0%	4000
Hydrogen	Sheddable		45.6%	4000
Industrial heating	Shiftable		13.2%	4000

Table 3
Scenarios.

Scenario name		Impact of weather variability		Investments based on extreme weather			Hydrogen price
Simulation name	Baseline (B)	Increasing demand (ID)	Stochastic profiles (SP)	Low vRES (EL)	Median vRES (EM)	High vRES (EH)	High hydrogen price (HH)
Weather profile year for investment	Median vRES	Median vRES	Median vRES	**Low vRES**	**Median vRES**	**High vRES**	Median vRES
Number of weather years for dispatch	1	1	40	40	40	40	40
Weather profile years for dispatch	Median vRES	Median vRES	**stochastic**	stochastic	stochastic	stochastic	stochastic
Number of simulations	1	1	10	1	1	1	1
Demand increase	no	**yes**	no	no	no	no	no
Hydrogen price	45 €/MWh	45 €/MWh	45 €/MWh	45 €/MWh	45 €/MWh	45 €/MWh	**90 €/MWh**

is caused by the absence of imports/exports in the ABMs. Cross-border trade can greatly contribute to the reliability of neighboring countries resulting in less installed capacity. We simulate the Netherlands as an island because modeling all dimensions of power system models (space, complexity, and time) would be too computationally intensive for the purpose of this study.

The initial power plants are assigned evenly distributed ages to be gradually replaced. Photovoltaic (rooftop and utility system), wind onshore, wind offshore, lithium batteries, biomass, and hydrogen turbines are potential investment technologies.

4.2. Scenarios

In all simulations, investment costs, fuel, and CO_2 prices are constant (see Tables 9–11) present the rest of the data used in each scenario. In all simulations, we considered one agent investor, as the purpose is to study weather impact rather than dynamics with different types of investors. Each simulation is executed for a simulation horizon of 40 years. We use a combination of scenarios to study the impact of weather variability, the impact of basing investment decisions in different weather years, and the impact of hydrogen prices on future system adequacy. Table 3 presents an overview of the simulations.

4.2.1. Weather impact simulations

It is our impression that energy producers tend to estimate future cash flows by multiplying the expected energy yield times the expected electricity prices, either for a single scenario or for a handful of electricity price estimations, as described in [75]. Price cannibalization[5] can be estimated using a regression equation that represents the relationship between an increasing share of vRES and decreasing prices, as explained in [76].

In EMLabpy, to resemble a risk-neutral agent (who considers P50 for investments), investment decisions are based on a weather year with a median renewable production. An alternative is to select the year in which the market revenues are median, but these revenues are highly dependent on the number of scarcity hours. A fixed capacity mix from ABMs (as described in Section 4.1.5) is evaluated with 40 yearly vRES profiles (augmented from 1980 to 2019) and the corresponding demand profiles. The year with a median renewable energy production is 2004, which we select as the representative year.

In the long run, dependence on weather may cause higher uncertainties than demand growth. Both uncertainties are compared as follows. In the Baseline scenario (B), the actual weather profiles serve as the basis for investors' decisions, granting them perfect foresight. In a second benchmark scenario, the demand and weather profiles remain constant but demand presents a stochastic Increased Demand (ID). In this scenario, demand increases with a triangular trend, as done in [22] (min= 0.99, max=1.03, and mode=1.02). The future demand is estimated with simple linear regression from the last three years.[6] Finally, in the Stochastic Profiles (SP) scenario we run ten simulations with no increase in demand, but with varying weather profiles. Every year, the market clearing is based on randomly selected historical weather profiles, whereas investment decisions are based on a representative year, as shown in Fig. 3.

4.2.2. Investments based on extreme weather

To compare the effects of investors' risk adversity, we analyze investment decisions based on three extreme energy yield estimations. These scenarios are a year with the Energy yield Low (EL), the Energy yield Median (EM), and the Energy yield High (EH). In particular, 2010 was the year with the lowest production of renewable energy, while 1990 was the year with the highest production.

4.2.3. Hydrogen price

Finally, we simulate a scenario where the hydrogen price was double than the one used in the rest of the simulations, which was based on the ENTSO-E global ambition scenario [69].

4.3. Key performance indicators of the results

To compare the results of the co-simulation we use the following Key Performance Indicators (KPI) and their inter-annual variability

[5] Market value reductions as a function of the technology's market share.

[6] For investments made within the initialization loop, the assumption is that the demand increases with the rate of the mode.

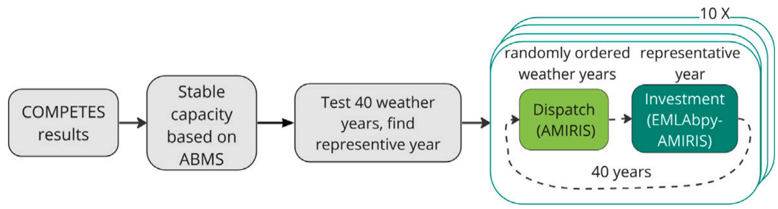
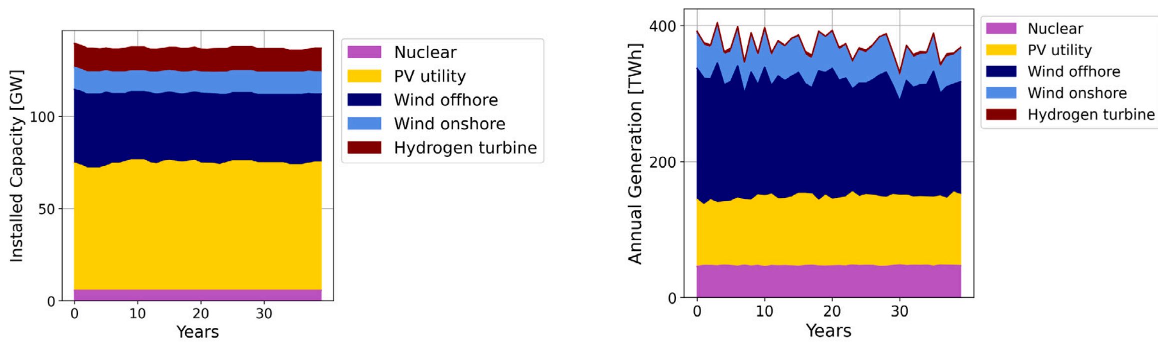


Fig. 3. Stochastic profiles simulations' workflow.



(a) Annual installed capacity per technology

(b) Annual generation per technology

Fig. 4. Yearly installed capacity and generation by energy technology.

(coefficient of variance). The KPIs are used to assess the overall system and performance by technology.

- Adequacy KPIs
  - Energy Not Served (ENS) (MWh/year): Energy that is not supplied due to insufficient capacity resources to meet the inflexible demand.[7]
  - Loss Of Load Expectation (LOLE) (hours/year): Number of hours in which resources are insufficient to meet the demand
  - Hydrogen production (MWh): Power consumed by electrolyzers to produce hydrogen
- Financial KPIs
  - Monthly average electricity prices (€/MWh)
  - Weighted averaged yearly electricity prices (€/MWh)

$$WAVGprices_y = \frac{\sum_{t=1}^{t=8760} prices_t \cdot Generation_t}{\sum_{t=1}^{t=8760} prices_t} \tag{7}$$

  - Cost recovery (%): Yearly total market cost recovery,

$$CostRecovery = \frac{Rev}{CapEX + VC + FC + A} \tag{8}$$

where the ideal would be for generators to recover 100% of their investments.

5. Results and discussion

In this section, we first analyze the installed capacity and price dynamics of a single stochastic profile simulation. Then we contrast the adequacy and financial KPI in the three scenarios considering weather variability (B, ID, and SP). Next, we analyze the results of simulations in which investors base their investment decisions on extreme weather profiles. Following this, we analyze a simulation with higher hydrogen prices. Finally, we draw the main policy implications of the study presenting the main limitations of the model and future research.

5.1. Impact of weather variability

5.1.1. Installed capacity

Since the investment algorithm was based on the same weather year throughout the whole simulation, the generation mix remained relatively constant (see Fig. 4(a)). Investment costs for wind offshore are expected to be 4 times larger than those of PV (Wind offshore capital costs are 1,444 €/kW compared to PV capital costs of 350 €/kW, see Table 10), as a result, solar PV energy composed the largest proportion of the portfolio. In contrast, offshore wind total generation was 30% higher than solar generation, as it has a higher capacity factor (Wind offshore capacity factor is 51%, in contrast to 16% from solar PV).

The high proportion of flexible load (primarily from electrolyzers) reduced the number of hours during which electricity prices were low. For this reason, the arbitrage opportunity for lithium battery storage was reduced and no investments were made in this technology. In AMIRIS, the representation of multiple flexibilities is limited, and technical details, such as ramping constraints, are not considered. Therefore, dispatchable technologies were considered more flexible than they actually are. As a result, nuclear energy was overestimated, while the need for rapid response technologies like batteries was underestimated.

5.1.2. Electricity price dynamics

Nowadays the price in electricity markets is mainly driven by generators's marginal costs. In future power systems, the disparity between the near-to-zero marginal cost of vRES and that of fuel-based technologies will continue to exist. However, electricity prices will be mostly set by flexible demand. Hydrogen will be produced when prices are below the hydrogen market price. Similarly, the industrial heat demand will be satisfied when prices are below the costs of using natural gas boilers. Fig. 5 illustrates the price duration curve for one year, with each color

[7] Does not include the energy not served by electrolyzers.

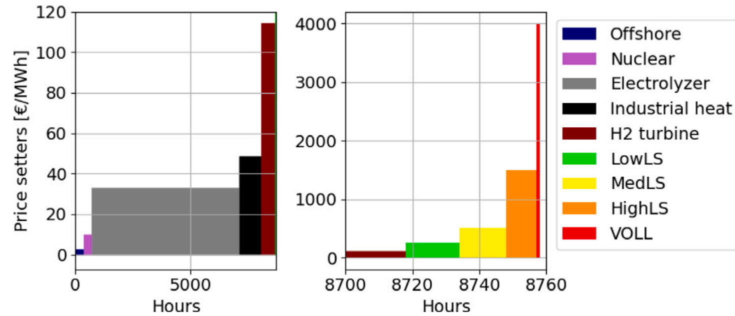


Fig. 5. Price setting technologies in year of a SP simulations.

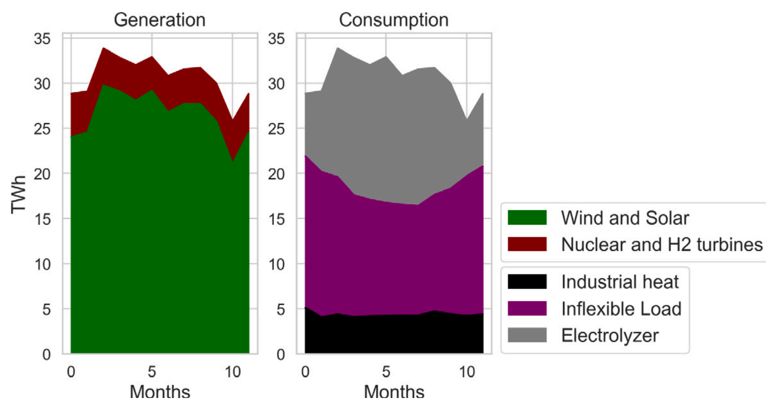


Fig. 6. Monthly generation and consumption of a SP simulation.

representing the price-setting generator or demand. Electrolyzers and industrial heat demand set the price most of the time.

Although we modeled a highly flexible system, there was not sufficient investment in flexible resources to prevent shortages in years with high demand and low vRES production. During the winter, heat pumps increased demand during periods of low renewable energy production, resulting in involuntary load-shedding despite a decrease in hydrogen production (see Fig. 6). This occurs even though the industrial load was totally flexible. In practice, industrial processes may not be able to completely switch between using electricity and other fuels, nor may they be able to shift the load for extended periods of time.

Analyzing the monthly average electricity prices, we observed a large disparity between the winter months and the rest of the year. For instance, in June average electricity prices were 33.9 €/MWh, whereas in January the average went up to 71.2 €/MWh, (see Fig. 7). Extreme average monthly prices above 150 €/MWh were repeatedly seen as a result of a correlation of low vRES and low temperatures. This indicates that future vRES-based power systems will require long-term storage (both thermal and electrical), demand-side flexibility, and mechanisms that incentivize them.

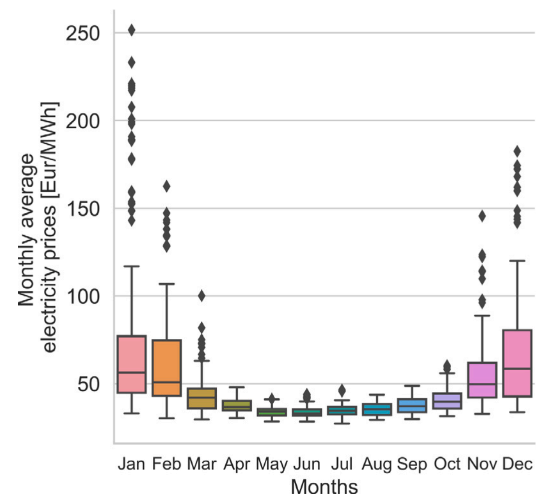


Fig. 7. Monthly average electricity prices of stochastic-profiles simulations.

5.1.3. Adequacy KPIs

The adequacy of future systems will be vulnerable to weather variations. While in the baseline scenario and the increasing-demand scenarios, the average LOLE was 3 h per year, in the SP scenario, shortages increased to an average of 6.7 h (see Table 4). This is more than the current LOLE standard in the Netherlands, which is 4 h per year [77]. The average LOLE in SP scenarios was almost twice the current standard, but in the worst year, the shortages went up to 48 h. This reveals that an EoM design might hinder the system's adequacy as the capacity will not be able to guarantee sufficient supply in the years with low vRES.

Shortages were the main cause of higher electricity prices and cost recovery. As shown in Fig. 9, the years with the highest shortages and ENS were also the years with the highest electricity prices and years with the highest cost recovery. In contrast, years with high vRES energy yield worsened the cost recovery. The yearly cost recovery of the total system consists of market revenues and costs, including down payments and loans. In the years when there were more power plants under construction, down payments caused a minor decrease in cost recovery, as shown in Fig. 8. Note that a share of loans remained constant, which corresponds to the loans of nuclear plants that were not decommissioned.

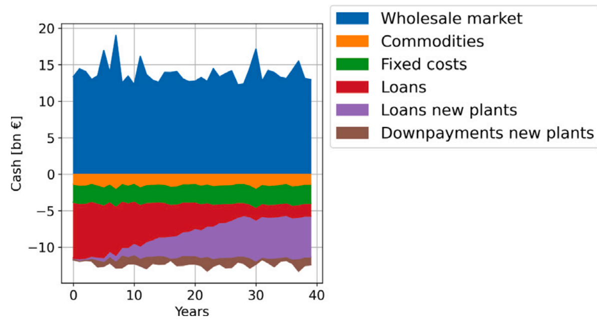


Fig. 8. Total revenues and expenses in a SP simulation.

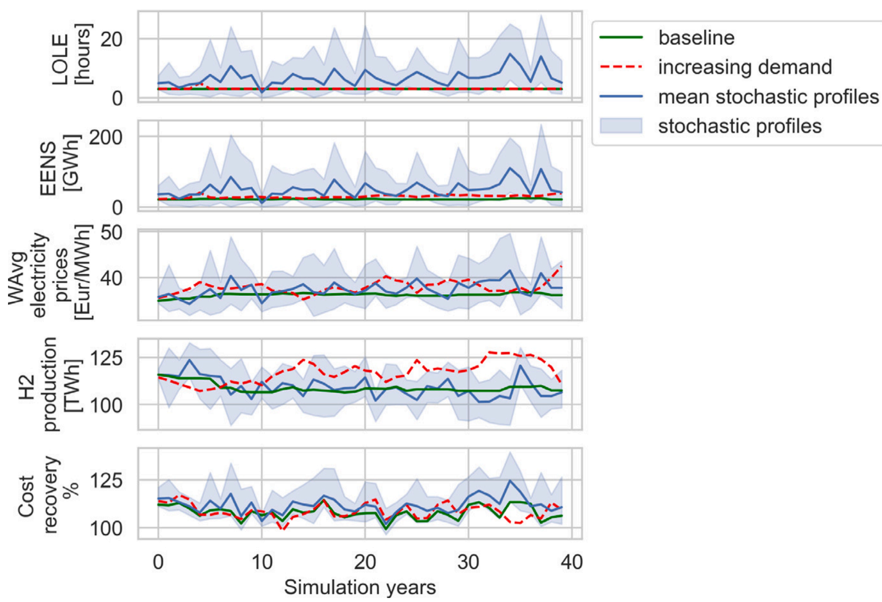


Fig. 9. KPIs in the Baseline scenario, in the ID scenario, and the SP scenario in the realized dispatch.

In scenario ID, higher demand levels required an increase in installed capacity, resulting in an increase in hydrogen production, from 147 TWh in simulation B to 158 TWh in simulation ID. However, the inter-annual variability increased by a factor of more than 2 in the ID simulation and by a factor of more than 5 in the SP simulation (see Table 4).

5.1.4. *Financial KPIs*

The Coefficient Of Variance (COV) for the weighted-average annual electricity prices increased from 1% under simulation B to 4% in the ID simulation 13% in the SP simulations. The COV of monthly electricity prices increased from 32% in simulation B to 35% in the ID simulation, and to 48% in the SP simulations.

In the SP scenarios, the cost recovery volatility was more than three times that of the scenario with no weather stochasticity (from 3% to 9% COV). The average cost recovery increased from 108% in the Baseline scenario to 109% in the ID scenario and 112% in the SP scenario. Nevertheless, the highest cost recovery in a single year rose to 148%, reflecting the windfall profits that would occur due to prolonged shortages. Scarcities in years with low vRES and the resulting high electricity prices allowed producers to recover their costs but caused high volatile returns and high volatile monthly average electricity prices.

In years with low renewable yield and high electricity prices, hydrogen production was relatively low. The electrolysis production in the stochastic-profiles scenario ranged between 94 and 148 TWh and its volatility (11%) was five times that of the fix-profiles scenario (2%). In these simulations, a fixed hydrogen price was assumed; however, the hydrogen price will be very dependent on the H_2 interconnections, storage capacities, and the flexibility of other sectors. Furthermore, the volatile electrolyzers' operation would impact the price of hydrogen. If hydrogen resources are insufficiently diversified or interconnections limited, a year with low renewable energy would result in lower H_2 production and high hydrogen prices. As hydrogen turbines would be dispatched at a higher cost, electricity prices could rise even further. Calculating the IRR over the entire lifetime of new power plants (for plants that are built and decommissioned during the simulations), H_2 turbines presented the highest and most volatile returns, followed by wind onshore, offshore, and PV (see Fig. 10). Since dispatchable technologies were operational during most scarcity events, they generated the majority of their revenue during these instances. In contrast, vRES did not always operate during scarcity hours and therefore did not

Table 4
Adequacy and financial KPIs of simulations about the impact of weather variability.

			Baseline	Increasing demand	Stochastic profiles
ENS	MWh	mean	22,495	30,072	50,359
		COV	5%	14%	119%
		min	21,762	22,868	0
		max	24,786	40,690	392,416
LOLE	hours	mean	3.0	3.1	6.7
		COV	0%	10%	113%
		min	3	3	0
		max	3	5	48
Yearly WAVG electricity prices	€/MWh	mean	36	38	37
		COV	1%	4%	13%
		min	35	35	31
		max	37	43	57
Monthly average electricity prices	€/MWh	mean	44	46	46
		COV	32%	35%	48%
		min	31	31	27
		max	88	113	252
Hydrogen production	TWh	mean	147	158	148
		COV	2%	5%	11%
		min	144	145	103
		max	157	173	189
Cost recovery	%	mean	108	109	112
		COV	3%	4%	9%
		min	99	98	94
		max	114	117	148

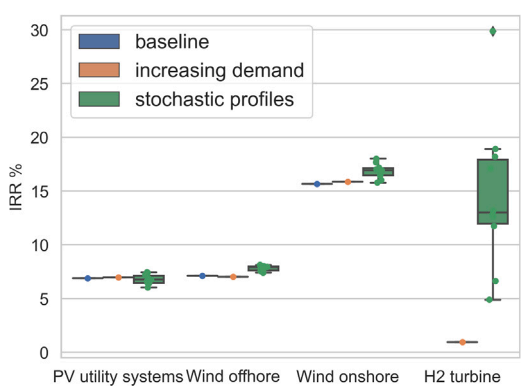


Fig. 10. IRRs of new plants under SP scenarios.

receive these scarcity rents. For this reason, the inter-annual volatility of vRES's profits was smaller.

As described in the previous section, the total cost recovery was higher in the ID scenarios and even higher in the SP scenarios. Nevertheless, the hydrogen turbine had remarkably high volatile returns. In one simulation, the hydrogen turbine operational profits were negative for five consecutive years[8] (see Fig. 11), and also very high in some years. The profitability of all technologies, particularly that of hydrogen-fueled technologies, can be even more volatile as hydrogen price is unlikely to remain constant. This poses the question of whether financial instruments would exist for a technology that may be unprofitable for some consecutive years. Furthermore, the nuclear plants' operational profits were consistently the most negative and volatile (see Table 13). This illustrates that in a highly flexible system, where electrolyzers with low opportunity costs largely determine prices, base load technologies may struggle to recoup their expenses.

Out of the vRES technologies, solar energy showed the lowest average profits, which is due to the cannibalization effect. The investment algorithm frequently invested in this technology, but subsequent investments diminished their profitability. The anticipated high profits from onshore wind would have encouraged additional onshore investments, but its technical capacity limit (12 GW) [78] was reached. Hence, it presented the highest returns among the vRES technologies.

5.2. Investments based on extreme weather years

Choosing the median weather year when making investment decisions resembles the behavior of risk-neutral investors. In practice, investors tend to be risk-averse and rather conservative when estimating the renewable yield. We ran two additional simulations where the realized dispatch was based on stochastic weather years, but the investment algorithm was based on a year with an Energy yield High (EH) vRES production (1990) and an Energy yield Low (EL) vRES production (2010) for the investment algorithm.

In EH scenario, the installed capacity was 121 GW, i.e. 11.1% less capacity than considering the median vRES (see Fig. 12). The reduced investments caused scarcities (37.8 h on average), high weighted average electricity prices (44 €/MWh on average), and led to a high-cost recovery (133% on average). In this case, the hydrogen turbine generators obtained extremely high returns (see Table 6), due to the frequent shortages. Alternatively, if investment decisions were based on an EL year, investments added up to 150 GW, i.e. 9.9% more capacity than with median vRES yield. The weighted average electricity prices were lower (37.4 €/MWh on average), and market revenues were insufficient to cover the costs (cost recovery is 98% on average). In this scenario, only wind energy generators recovered their investments, and the wind onshore presented the highest returns (see Table 6). The algorithm would have invested more in this profitable technology but the technical potential was quickly reached. The offshore wind energy yield was the most variable among vRES technologies, so considering a year with high renewable energy yield led to a portfolio with a higher share of wind offshore, even if the total capacity was smaller. Investing based on a high-vRES yield resulted in the installation of 49 GW of wind offshore, compared to 37 GW when using the median return profile and 34 GW when using the lowest return vRES profile.

[8] In cash flow calculations, the down payments were registered during the building time and not considered in operational profits

Table 5
Investments considering extreme weather years.

		Low vRES	Median vRES	High vRES
Installed capacity	GW	151	137	122
ENS	Avg [MWh] COV	3858 244%	50888 123%	286601 87%
LOLE	Avg [hours] COV	0.5 231%	6.8 115%	37.8 80%
Yearly WAVG electricity prices	Avg [€/MWh] COV	33.5 9%	37.4 14%	44.2 22%
Monthly electricity prices	Avg [€/MWh] COV	40.4 27%	45.7 49%	62.1 79%
Hydrogen production	Avg [TWh] COV	148 11%	148 12%	171 13%
Cost recovery	Avg [%] COV	98.6 5%	111.8 10%	133.4 17%

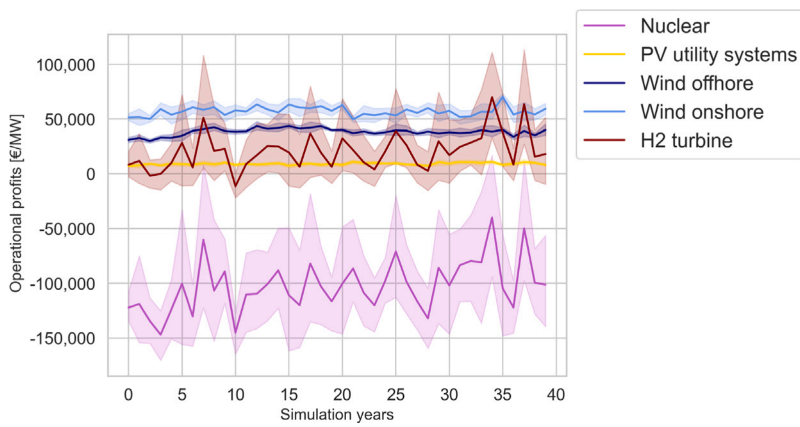


Fig. 11. Annual operational profits per MW in the stochastic-profiles scenario.

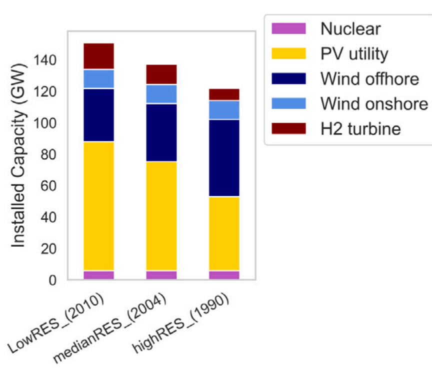


Fig. 12. Last simulation year installed capacity in scenarios where investments were based on extreme weather years.

Electrolyzers' activation depended on the number of hours in which the electricity price was less than the market price of hydrogen. In the simulation with high-vRES, offshore wind energy share in the capacity mix was greater, resulting in more hours with low electricity prices and thus, more arbitrage opportunities for electrolyzers (see 5). For this reason, hydrogen production increased in the high-VRES simulation, even though less capacity was installed overall.

Table 6
Average IRR per technology with extreme weather investments.

Technology	Low RES	Median RES	High RES
PV utility	−1%	6%	13%
WTG Onshore	16%	18%	22%
Hydrogen turbine	–	19%	99%
WTG Offshore	7%	8%	9%

		Base	Double HH_2 price
Installed capacity	GW	137	172
ENS	Avg [MWh] COV	50 888 123%	71 214 93%
LOLE	Avg [hours] COV	6.8 115%	9.5 89%
Yearly weighted average electricity prices	Avg [€/MWh] COV	37.4 14%	43.4 16%
Monthly average electricity prices	Avg [€/MWh] COV	45.7 49%	57.1 42%
Hydrogen production	Avg [TWh] COV	148 12%	273 8%
Cost recovery	Avg [%] COV	111.8 10%	127.2 10%

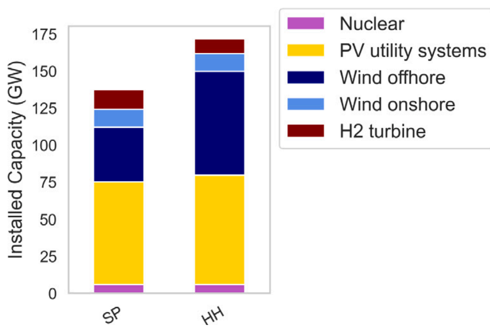


Fig. 13. Final Capacities of one SP and high hydrogen price simulation.

5.3. Higher hydrogen price

Finally, an additional simulation with a hydrogen price twice as high demonstrated the double side effect of hydrogen prices. In this analysis, we assume that the price of hydrogen remains constant, although in reality, it will be strongly influenced by the annual vRES production. We also considered a fixed electrolyzer capacity; however, the installed capacity of electrolyzers will ultimately be influenced by the hydrogen price.

On one side a higher hydrogen price incentivized more investments, especially in wind offshore generators, which had a broader energy generation distribution than solar energy. The technical limit of wind offshore (70 GW) was reached in contrast to the 37 GW with lower hydrogen price, which raised the average profitability of offshore turbines from 8 to 15%. On the other side, it decreased the profitability of hydrogen turbines, deterred investment in these technologies, and exacerbated shortages. 10 GW of hydrogen turbines were installed, in contrast with the lower hydrogen price simulations, where 13 GW were installed (see Fig. 13)

Although the inter-annual volatility of shortages decreases, scarcity hours increased on average from 6.8 to 9.5 h per year. The reliability of a system was ultimately determined by the installation of sufficient peak-load dispatchable technologies. More installed capacity nearly doubled the power used by electrolyzers, to an average of 273 TWh and decreased its inter-annual variability. Similarly, average yearly prices also rose but their inter-annual volatility slightly increased. Finally, the cost recovery increased, as there was more generation at higher prices.

5.4. Policy implications

Our results show that future vRES-based energy systems with an EoM design will be susceptible to weather volatility. The uncertainty regarding energy supply will be larger than the current uncertainty regarding demand levels. This can cause large shortages and high inter-annual revenue volatility. As a result, investors can be expected to have difficulty financing investments with high CAPEX, as there will be a poor business case for generation and energy storage units that are only needed in unfavorable weather years. Moreover, as Neuhoff [79] explains, uncertain returns increase financing costs, decrease investments, and diminish consumer welfare. Therefore, the adoption of revenue-stabilization mechanisms is necessary both for achieving security of supply and for reducing the cost to consumers.

Regarding hydrogen production and system integration, Mikovits et al. [80] modeled a system where the wind power capacity covers on average the power demand for electrolyzers and found that a large capacity of wind turbines and electrolyzers can decrease the need for backup capacity. We found that the installed capacity of offshore energy will depend on the hydrogen price, and a larger share of wind offshore increases hydrogen production. However, we observed that the volume of dispatchable generation capacity ultimately determined the number of shortages.

Finally, a future market design should incentivize sufficient investment but also limit earnings in the case of prolonged high prices, as consumers suffer as much from the high prices during a prolonged shortage period as from the outages themselves. We observed that price spikes and adequacy requirements predominantly occur during cold months when heating needs arise. The significant monthly and inter-annual price variations due to weather volatility present another important challenge of the energy transition, which is consumer price protection. Highly volatile monthly electricity prices also highlight the need to ensure sufficient seasonal storage, demand flexibility, and energy system integration with energy vectors such as hydrogen. Market design can facilitate the investment of technologies with high capacity factors through CRMs. However, as [81] recognized, the estimate of the contribution of each technology to peak load, the estimate of values of lost load, the probability of peak load, and the probability of generation availability are becoming increasingly challenging.

5.5. Model limitations

In a future system, cross-border transmission can greatly influence the capacity that is required to meet adequacy standards, as imports can mitigate scarcity events. Astier et al. [81] demonstrate that reliability standards can lead to socially optimal results only if adequacy assessment assumptions are coordinated between neighboring countries. Ignoring cross-border trade can lead to overestimating electricity prices ([78] quantifies this effect to up to 40%), but it is uncertain to what extent countries are willing to rely on neighboring power supplies to ensure adequacy. However, in our co-simulation of two ABMs, modeling multiple European countries would have been computationally infeasible. Therefore, we did not consider internal or cross-border transmission constraints. Furthermore, the model does not consider sector coupling, resulting in a capacity mix different from the optimization results.

Finally, it is worth mentioning two additional factors not analyzed in this study that could further compromise the reliability of the system. Nowadays, a minority of outages are caused by insufficient installed capacity, while distribution and transmission inefficiencies and the correlation of extreme weather events with infrastructure failures have been the main reasons for the most serious shortages [26]. Furthermore, extreme weather events are expected to intensify due to climate change effects. With fatter distribution tails, building sufficient backup capacities will also be more relevant.

5.6. Lessons from co-simulating

Co-simulating can be time-intensive, as it requires careful coordination and data management among the involved models. However, it also allows the utilization of a subset of the data in each module as needed. As portions of the problem are divided, this can keep the computation size manageable for simulations spanning multiple decades. Moreover, developing models in a modular manner can allow reusability and parallel model development. The ABMs applied here are built in a way to allow coupling with other models.[9]

[9] In EMLabpy all parameters and inputs are modifiable in a spreadsheet format

5.7. Future work

In this analysis, we used a fixed weather year for the investment decisions and fixed fuel prices. Future research will focus on the transition pathway, where investors do not have complete certainty on the decommissions, fuel prices, and most importantly the CO_2 price. Further, transition scenarios towards 2050 incorporating policy interventions such as capacity remuneration mechanisms and renewable energy support will be investigated.

6. Conclusions

We presented a co-simulation of an agent-based model of myopic, profit-seeking investors with an operational ABM that simulates the power market on an hourly basis. With this model set-up, we simulated model-endogenous investments in a future, zero-carbon energy system, while considering the variability of renewable energy as well as energy storage and demand flexibility, in order to assess system adequacy in such a system. We performed our analyses for an energy-only market, i.e. a market in which the price of energy drives investment.

We found that in a market based on vRES, the price will be set predominantly by the flexibility of demand, in particular electrolyzers' demand. The production of hydrogen can keep electricity prices above zero and lower than the market price of hydrogen. Despite this flexibility, the high demand caused by heat pumps during the winter months led to prices that were twice as high as in the summer. In years with low vRES production, power shortages occurred, primarily in winter. For this reason, dispatchable technologies, including long-term storage and thermal storage will become increasingly important to ensure reliability. In our simulations, dispatchable technologies had the most volatile financial returns, confirming the intuition that investing in these technologies is becoming riskier. These dispatchable technologies will be crucial to meet demand, but the business case for providing the marginal facilities, the ones that only are needed in unfavorable weather years, is poor.

The energy sector is currently confronted with uncertainty regarding future fuel prices, technology costs, energy demand, system flexibility, policy interventions, and the introduction of new technologies, among others. Even if we simulated a steady-state scenario for a fully decarbonized energy system in which demand, fuel prices, and the CO_2 price were stable, investment cost recovery would remain uncertain due to the large impact of inter-annual weather variability. We compare the impact of weather uncertainty with the uncertainty from stochastic demand growth and observe that even in a very flexible system, shortages are higher in scenarios with weather variability. In our simulations, the inter-annual variability of cost recovery increased more than three-fold, and annual variability of weighted-average electricity prices more than ten-fold, in comparison with a scenario without weather uncertainty.

An interesting finding was the impact of the weather year that investors use for deciding upon new generation capacity. We demonstrated that if investors based their investments on a weather year with very low vRES, thereby ensuring the reliability of the system for the worst weather years, they would be unable to recover their investments. On the other hand, if they would base their investment decisions on a more optimistic vRES yield, they would invest less and receive excessive returns, but this would come at the cost of lower system reliability and higher electricity prices. We conclude that in a system with intermittent supply, investors have insufficient incentive to ensure reliability, and therefore a capacity remuneration mechanism will be needed to ensure enough backup capacities. In future studies, we will investigate the performance of capacity mechanisms, as well as the performance of CRMs in the course of the power systems transition to a vRES-based system.

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CRediT authorship contribution statement

I. Sanchez Jimenez: Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **D. Ribó-Pérez:** Writing – original draft, Supervision, Methodology, Investigation, Data curation, Conceptualization. **M. Cvetkovic:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **J. Kochems:** Writing – review & editing, Software. **C. Schimeczek:** Writing – review & editing, Software. **L.J. de Vries:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

The conceptual and data workflow are shown in Figs. 14 and 15. See Tables 9–14.

Table 9
Fuel prices at year 2050 Global ambition. H_2 price is the renewable H_2 imports price in [69,82].

Fuel	Price
CO_2 [€/ton]	168
Natural gas [€/MWh]	14.65
Hydrogen [€/MWh]	45.1
Biomass [€/MWh]	35

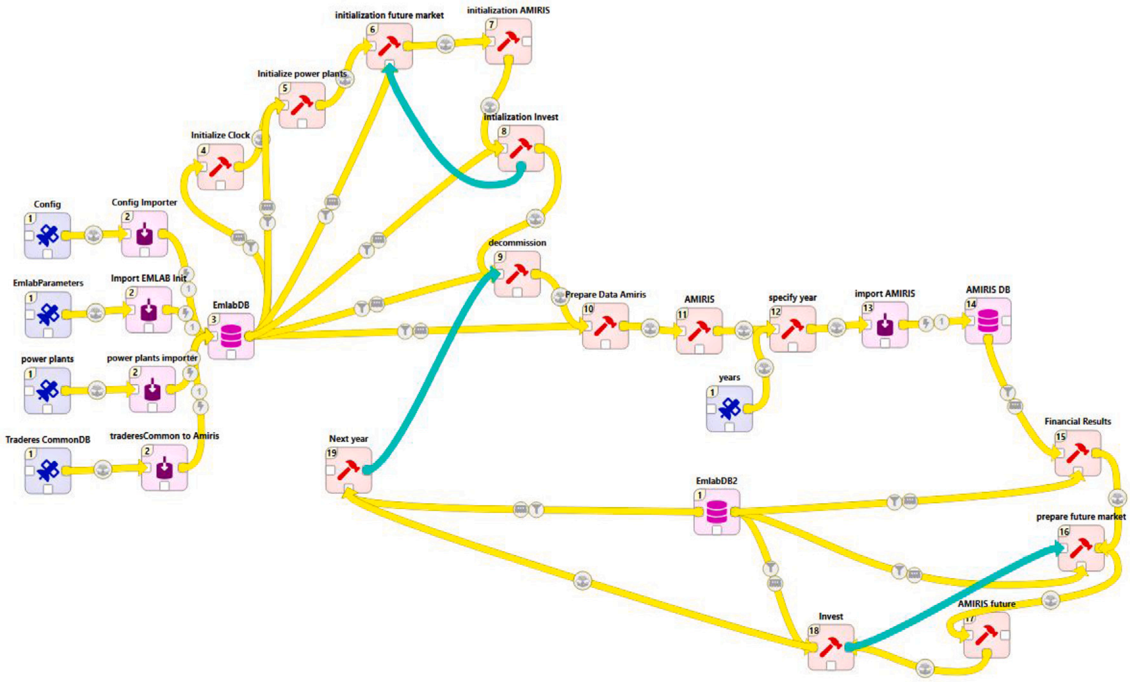

Fig. 14. Workflow in Spinetoolbox.

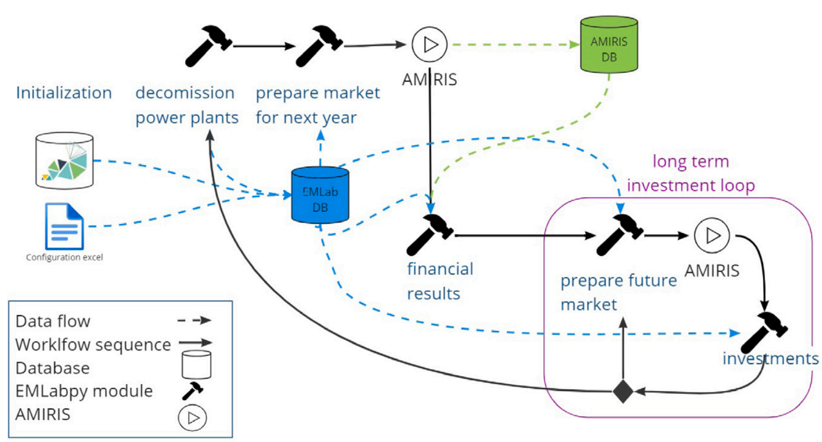

Fig. 15. Data workflow.

Table 10
Technology costs at year 2050 [69,82].

	Investment costs [€/MW]	Variable costs [€/MWh]	Fixed costs [€/MW/year]	Efficiency [%]
Lithium ion battery	€ 1,020,000	1.8	800	0.90
WTG offshore	€ 1,444,000	3	24 700	
PV utility systems	€ 350,000	0	7600	
PV residential	€ 688,000	0	11 000	
WTG onshore	€ 1,127,000	1.35	12 900	
Biomass CHP	€ 2,040,000	1.9	50 000	0.31
Hydrogen turbine	€ 435,000	1.5	8700	0.40
Nuclear	€ 6,000,000	4	100 000	0.29

Table 11
Technology data.

Technology	Realistic capacity [MW]	Permit time [y]	Construction time [y]	Lifetime [y]
Lithium ion battery	100	0	1	20
WTG offshore	500	1	2	30
PV utility systems	350	1	1	25
PV residential	300	1	1	25
WTG onshore	250	1	1	25
Biomass	300	1	3	30
Hydrogen turbine	500	2	2	30
Nuclear	1000	2	5	45

Table 12
Capacity factors and technology potential for vRES [61,78,83,84].

	Min capacity factors [%]	Max capacity factors [%]	Technology potential [GW]
WTG onshore	32	58	12 000
WTG offshore	43	60	70 000
PV residential	15	18	26 964
PV utility systems	15	18	82 099
Biofuel			12 040

Table 13
Operational profits per MW by technology.

Scenario	Fix-profiles		Increasing-demand		Stochastic-profiles	
Technology	$\bar{x}$	σ	$\bar{x}$	σ	$\bar{x}$	σ
Nuclear	−118,376	5970	−99,443	15,668	−102,579	70,160
PV utility	9,013	449	9173	978	9,076	2810
WTG Offshore	35,619	2,752	35,938	3,999	38,284	6,092
WTG Onshore	53,705	1,828	55,214	3,897	57,049	10,267
Hydrogen turbine	368	4,647	5,907	9,730	20,527	48,219

Table 14
Yearly average IRR per technology.

	$\bar{x}$ stochastic-profiles	High hydrogen price
PV utility	7%	4%
WTG Onshore	17%	22%
Hydrogen turbine	15%	–
WTG Offshore	8%	15%

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