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How do demand response and electrical energy storage affect (the need for) a capacity market?

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HIGHLIGHTS

- Impact of demand response-DR & electrical energy storage-EES in energy-only market.
- Analysing the impact of limited DR and medium-term EES on a capacity market-CM.
- Hybrid electricity market model allows realistic generation capacity investments.
- DR reduces the peak load which implicitly reduces requirements for the CM.
- Limited DR & medium-term EES lessens the case for a centralized CM.

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ABSTRACT

To ensure security of supply and incentivize reliable investment in generation capacity, capacity markets (CMs) have been implemented or are being considered. However, demand response (DR) and electrical energy storage (EES) also contribute to system adequacy. In this paper, we analyse the change in the need for a CM if DR and EES are available, in the presence of a growing portfolio share of intermittent renewable energy sources electricity (RES-E). We present a novel hybrid electricity market model of the transition to a low-carbon electricity system which uses optimization for short-term market operations and agent-based simulation of long-term decisions.

DR and EES may significantly reduce the risk of shortages in an energy-only market, even if investment decisions are myopic, like in our model, as compared to an energy-only market without flexibility options. We also present a novel mechanism for contribution of EES to the CM. This reduces the cost of the CM and improves the business case for EES. In our model, DR and EES achieve almost the same improvement of security of supply as a CM, but they do so at a lower cost. Therefore, the case for a centralized CM is weakened in a system with even a limited share of DR and medium-term EES, as presented in our model. These results depend on the duration of scarcity events and the cost of EES and DR. Refinement of the model representation will be required to extrapolate these conclusions to real markets with other types of DR, EES and CMs.

1. Introduction

1.1. Motivation & research objective

Transitioning electricity systems with a growing share of intermittent RES-E in the supply mix[1] increase the need for flexibility options like DR and EES in order to contribute to system adequacy. The European Commission [1] recommends that flexibility options like DR and EES should be considered to contribute to system adequacy. Capacity remuneration mechanisms (CRMs) ensure adequate level of generation capacity, provide adequate price signals for investment in generation capacity and facilitate the development of RES-E. Concerns that CRMs such as CMs [2–3] may be inefficient and distort trade between member states [1], gave rise to the question that to what extent flexibility options like DR and EES can reduce the need for a capacity mechanism such as CM. This question is addressed in this paper, together with a second question that emerged as part of this research, namely whether and how DR and EES should be remunerated by a CM.

We use EMLab-Generation, a hybrid agent-based – optimization model with agents making investment decisions to maximize future

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[1] Supply mix is the group of different energy sources from which electricity is produced.

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profits in an isolated uncongested electricity market (based on the Netherlands), including an endogenous CO_2 market and EES investment [4–7]. As our objective is to present a novel method for understanding the policy implications of DR and EES in an electricity system with a CM, we need to be able to model intertemporal constraints required for DR and EES. The existing version of model used in this paper and in past research did not have this functionality, as it used a load duration curve to clear the electricity market. Furthermore, we required a mechanism that enables EES to receive capacity credits in the CM. So we modified and extended EMLab-Generation, in order to improve the representation of short-term market dynamics, particularly intertemporal dependencies.

The core of the model, the electricity market clearing algorithm, has been changed entirely. The current model utilizes hourly demand data (time-series) instead of the previous load-duration curve and minimizes the cost of generation, carbon credits, EES and DR over the year. This enabled us to add intertemporal effects to the model, which are needed to assess the impact of intermittent renewables better and implement DR, EES and CO_2 market endogenously. Various modules of the model, including the power plant dismantlement, investment, the CM, bidding and annual payments (for electricity, capacity credits, carbon emissions credits, fuel) were modified/extended in order to respond to the detailed inputs/outputs from the hourly market clearing. An EES investment module was also added in order to better understand the business case for EES in the long term. Furthermore, we also present a mechanism for enabling the participation of EES in the CM to study its impact. We analysed six experiments with different combinations of policy instruments. Stochastic electricity demand growth and fuel prices trends were used in all experiments. Using this novel approach, we analyse an electricity market (with and without flexibility options), CM (with and without EES), and an investment market to study the transition of the power system with optimization and agent based modelling.

In the following sub-section, we review relevant literature and summarize how this paper contributes to the literature. Section 2 describes the methodology & modified hybrid version of EMLab-Generation, implementation of DR, EES, CM, generation capacity & EES investment along with input data and data analysis. Section 3 describes the experiments design. In Section 4, we discuss the model limitations and assumptions. In Section 5, we discuss and analyse the results along with sensitivity analysis and policy recommendations. The conclusions are discussed in Section 6.

1.2. Literature review

Past research has highlighted the importance of CRMs in light of social welfare loss, the missing money problem and decrease in resource adequacy, due to structural weaknesses in liberalized electricity markets. For example, generation adequacy challenges posed by the liberalization of electricity markets [8]; market failures and market barriers that prevent reduction in consumer costs [9]; the advantages and disadvantages of different CRMs [10]; a lack of adequate investment in generation capacity in liberalized markets [11]; the impact of market power abuse [12]; failure of reformed competitive electricity markets to reduce consumer costs and provide reliable supply [13]; challenges and alternatives for achieving long term security of supply in competitive wholesale electricity markets [14]; challenges for competitive wholesale and retail electricity markets to maximize social welfare and ensure adequate generation capacity investment programs [15]. Considering these issues, designs for optimal power/energy markets [16] and dynamic approaches to CRMs in competitive electricity markets [17] have been proposed.

Many countries have already implemented CRMs, including Spain [18–19], Germany [20], France [21–23], the UK [24] and the USA [25] or are planning to implement them. The performance of various CRMs has been studied and analysed. The Regulatory Assistance Project [26] discusses the compatibility challenges between market coupling and CMs. Rodilla and Batlle [27–28] discuss the failure of energy-only markets to ensure security of supply, making a case for implementation of CRMs. Finon [29–30], Newbery and Grubb [31–32] discuss the challenges in implementing an integrated European electricity market and coordinating CRMs. CMs and issues of generation adequacy are discussed and analysed by: Batlle and Rodilla [33], Cepeda and Finon [34], Cramton and Stoft [35], Genoese et al. [36], Vazquez et al. [37], Bhagwat et al. [38], Bothwell and Hobbs [39], Bushnell et al. [40], Höschle et al. [41], Fraunholz et al. [42], Zimmermann et al. [43].

The participation and the potential of DR in electricity markets has been discussed by many [44–48]. DR significantly contributes to US electricity markets through wholesale and retail DR programs by curtailing/shifting load [49–50]. PJM power system allows for DR participation in the wholesale day-head spot market trading [51]. Walawalkar et al. [52] give detailed insights on the impact of DR participation in PJM and NYISO electric power systems and the opportunities present for optimal DSM. DR has been included in CMs in PJM, ISO-NE and NYISO in the US through various programs [49,52–53]. Consumers are incentivized to curtail/shift consumption during summer (e.g. PJM) or winter (e.g. NYISO) peak load hours [3,54]. Genc [55] analyses the impact of DR on hourly electricity prices in the Ontario electricity market. Aalami et al. [56] summarize the participation of DR through load shifting/curtailing in various CM programs in the US and its impact on reducing consumer costs.

The potential of DR in Europe has been assessed by, among others, Finn and Fitzpatrick [57], Gils [58] and Warren [59]. Torriti et al. [60] discuss the experiences of UK, Italy and Spain with understanding the constraints as well as initiatives and policies for DR. A demand-based electricity distribution tariff in the residential sector has been introduced for increased DR in order to fully exploit the Swedish power system in intra-day market [61]. The Electricity Balance Adjustment Service or Elbas market has also allowed for DR trading in the intra-day market in Scandinavia [62]. The NEBEF mechanism in the French power system also allows trading of DR in the day-ahead market [23]. Eid et al. [63] summarize the participation of DR for electric flexibility trading. The impact of participation of DR in the German balancing mechanism has also been quantified by Koliou et al. [64]. The French power market is foreseeing DR trading in CMs in 2018 [65]. While the western countries are racing towards increased DR, Asia and the middle east represent the new frontiers for DR programs [66–68].

The participation and the potential of EES in electricity markets has also been discussed by many, focusing on two aspects: its importance in market economics and the value of EES to the power system [69]. Zakeri and Syri [70] present a comprehensive study on the comparative life cycle costs of various EES. The results show that the costs of deploying large-scale EES systems in electricity markets is too high and the business case of EES on utility scale is weak. However, vigorous research to bring these costs to a feasible level are underway, which leaves room for optimism for inclusion of utility-scale EES in future. Dunn et al. [71] discuss the available choices of batteries, suitable for storing electricity. Lithium is the material of choice for making efficient batteries [72–73]. Nevertheless, in order to realize a flexible and efficient liberalized electricity market, the importance of EES is widely recognized [70]. EES can charge during off-peak hours and discharge during peak hours to benefit from the price arbitrage in the intra-day and day-head market [74–76]. With integration of increased amount of intermittent RES-E, the spot market prices will become more volatile. This gives an opportunity for price arbitrage, adding to the profitability of EES [76–77]. The need for EES has been emphasized, even in the presence of a perfect transmission and distribution grid [78].

Various methods have been presented for analysing hybrid power systems, leading to a better understanding of participation of EES [79–82]. The potential of deploying large-scale EES in the PJM has been estimated and the results predict high revenues from spot market price arbitrage [83]. EES minimizes the effects of ramping, leading to more economical electricity production from nuclear power [84–85]. EES reduces the risks of overloading the transmission and distribution grid [75,86]. Many have analysed EES in regional power markets and the significant role of EES in future [69,87–91]. Contributions have also been made to analyse the collective impact of DR and EES on the integration of renewables, electricity grid and short term market dynamics [92–102].

Different modelling techniques are available for analysing electricity markets. Four most commonly used are: computable general equilibrium (CGE), system dynamics (SD), optimization and agent-based (ABM) [5,103–106]. A comparison of different techniques is given in Appendix A. ABM is only recently used for long term policy analysis [107–112].

Capacity markets have also been studied by using the modelling techniques mentioned above. Moghanjooghi [113] uses stochastic modelling to analyse long-term resource adequacy in energy-only markets. Optimization models have been used by Botterud et al. [114], Doorman et al. [115], Mastropietro et al. [116] and Dahlan et al. [117] to study the impact of CMs on security of supply. Cepeda and Finon [118], Petitet et al. [119] and Hach et al. [120] present system dynamics models for analysing CMs while Traber [121] and Ehrenmann and Smeers [122] use equilibrium models for their analysis. An agent-based model PowerACE analyses the impact of capacity payments on electricity prices and agent investment behaviour [36]. In terms of methodology and experiment design, the most comparable ABM to the current one has been presented by Keles et al. [123]. They provide a comprehensive analysis of market design options for the German electricity system including an energy-only market, CM and strategic reserve (with and without exogenous DSM capacity). Whereas, our objective is to study the impact of endogenous DR and EES on the need for a CM. Our research differs by: including DR and EES endogenously in the electricity market; bidding behaviour of agents in the CM and electricity market; EES participation in the CM; endogenous CO_2 market; endogenous investment in EES capacity and decommissioning of power plants on the basis of economic performance. Therefore, this work is important in order to study a novel market design option.

1.3. Choice of methodology

ABM is a highly suitable method for studying the out-of-equilibrium long-term effects of investment decisions such as path dependencies [124]. ABM enables the study of agents which make sub-optimal investment decisions due to with imperfect foresight and bounded rationality [125]. These conditions are expected to hold for investment decisions in the real world. A detailed comparison of ABM with optimization and equilibrium models can be found in Iychettira et al. [110]. Descriptions of the earlier version of EMLab-Generation that was used to study long-term effects on security of supply, the integration of renewables and carbon market in electricity markets are available in Bhagwat et al. [126], Iychettira et al. [110], Richstein et al. [5] and Richstein et al. [6–7].

2. Methodology

2.1. Description of modified/extended model

2.1.1. Introduction

This section briefly describes the modified/extended version of EMLab-Generation. For details, the description refers to past publications. The model is characterised by agents (power producers) [4] and an EES agent who make tactical investment decisions in generation and EES capacity, and bid into the market [127]. The computation time of the model, which is 40 years with 40 simulations per experiment, is kept under an acceptable threshold by making simplifying assumptions for the electricity market. The model is simulated for a time step of one year, within which the electricity market is cleared on hourly basis. Power production and EES companies make decisions regarding market bidding, procure fuels according to production, pay for CO_2 emission credits and decide on long-term investment [111]. Details of power plant operation and spot market bidding can be found in Richstein et al. [5].

The agents expect revenues on the basis of past market data, the expected supply in market with limited foresight. The agents interact with each other and the environment, affecting their cash balance and market position. The behaviour of power producing companies, other agents such as fuel suppliers, and all other modules (as described in detail in Richstein [111]) are implemented in Java. The model uses AgentSpring modelling framework [128] and is an extension and modification of Chappin [109]. The source code and input data used to run this model is openly accessible.[2]

2.2. Model structure

The agent decisions (regarding investment in generation capacity) are taken every year, after the market is cleared on an hourly basis. After market clearing, a load duration curve [129] is calculated for 20 segments (or load blocks) to capture the variation of load over the year, as shown in Fig. 1, which is used for investment decisions in generation capacity by the power producing agents to meet future demand.

Each year, the agents determine the fuel mix of their power plants (in case multiple fuels are required) [111], buy fuels, determine their bids for the power exchange and after the market is cleared, they dispatch their generation. They receive revenues from the spot market and pay any applicable policy cost (CO_2 price) or get paid (e.g. capacity credits from CM). While agents invest in and decommission power plants, the supply mix is an emergent result of the decisions they take in each year [111].

Fig. 2 describes a stylized model flow over the course of one year, including CM clearing. A detailed flow chart of the model for a year is described in Appendix C.

2.3. Electricity spot market clearing algorithm

The market clearing module is formulated as a linear optimization problem in Java and solved using the CPLEX solver [130]. A country allows for participation of one EES unit and DR program in the electricity spot market. A brief description of the optimization model is as follows:

2.3.1. Objective function

The objective of market clearing in the model is to minimize the cost of dispatch or marginal cost of generation per hour for the system as a whole. The objective function is given in Eq. (1).

$$Minimize \sum_{i}^{n} \sum_{t}^{n} MarginalCost_{i,t} * Generation_{i,t} \tag{1}$$

where time 't' = 1, 2, …, 8760.

where 'i' is the power plant, $MarginalCost_{i,t}$ is the marginal cost of generation of a power plant in €/MWh at time 't' and $Generation_{i,t}$ is the electricity generated by the power plant in MWh at time 't'.

2.3.2. Constraints

The following constraints are applied for clearing the spot market:

Power balance constraint: the total electricity generation should balance the total electricity demand:

[2] See https://github.com/asmkhan/emlab-generation/.

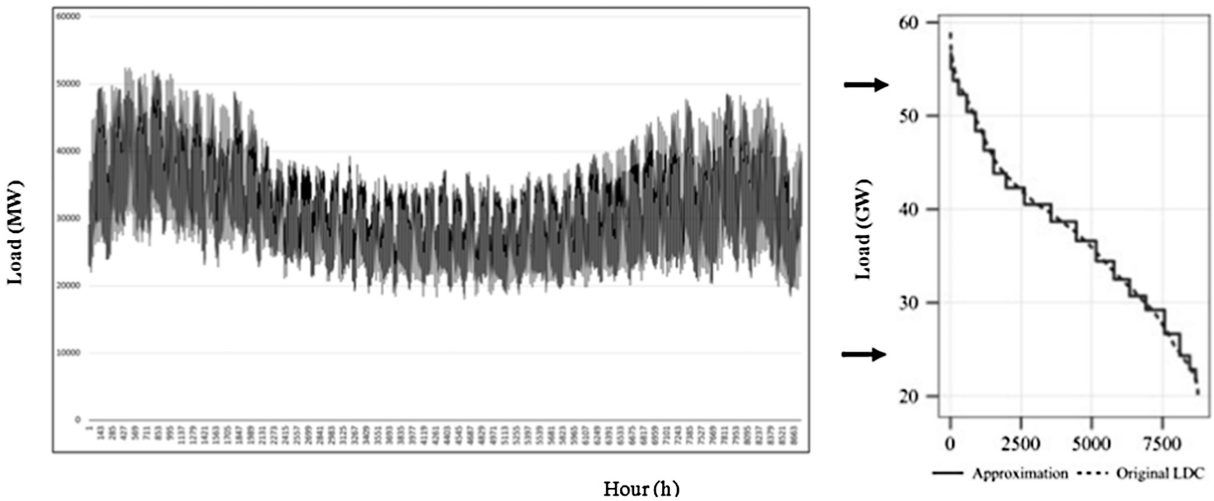

Fig. 1. Conversion of time series load data into load duration curve. Adapted from Richstein et al. [5].

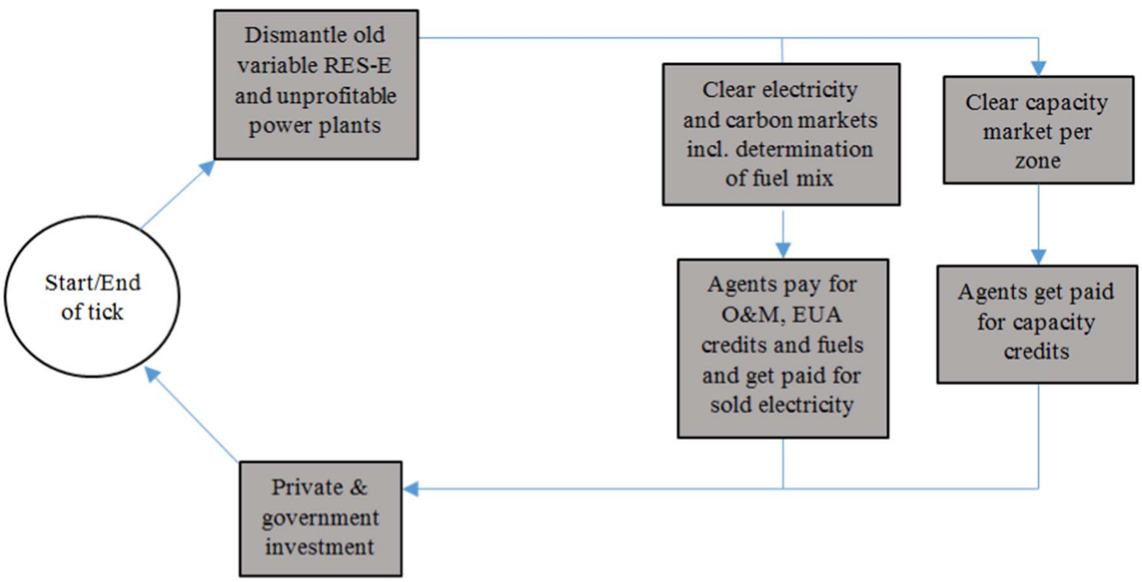

Fig. 2. Stylized model flow diagram of a year in the model.

$$\sum_{i}^{n} (Generation(thermal)_{i,t}) + \sum_{i}^{n} (Generation(RES)_{i,t}) + StorageDischarging_t = StaticDemand_t + ElasticDemand_t + StorageCharging_t \quad \forall\, t \tag{2}$$

where $Generation(thermal)_{i,t}$ is the electricity generated by thermal power plant 'i' in MWh at time 't', $Generation(RES)_{i,t}$ is the electricity generated by power plant 'i' using renewable fuel in MWh a time 't', $StaticDemand_t$ is the inelastic demand of electricity in MWh at time 't', $StorageCharging_t$ is the amount of energy charged in the storage unit in MWh, $StorageDischarging_t$ is the amount of energy discharged from the storage unit in MWh and $ElasticDemand_t$ is the elastic demand of electricity (shiftable) in MWh at time 't'.

The above equation can also be re-written as:

$$\sum_{i}^{n} (Generation(total)_{i,t}) = Demand(total)_t \quad \forall\, t \tag{3}$$

The dual value of the constraint in Eq. (3) gives the hourly electricity price in €/MWh for the zone.

Power generation limits: the electricity generated by a power plant should be within the generation capacity of that plant in any given hour:

$$0 \leqslant Generation(thermal)_{i,t} \leqslant MaxGeneration(thermal)_{i,t} \quad \forall\, i,t \tag{4}$$

$$0 \leqslant Generation(RES)_{i,t} \leqslant MaxGeneration(RES)_{i,t} * RESAvailability_t \quad \forall\, i,t \tag{5}$$

where $MaxGeneration(thermal)_{i,t}$ is the maximum amount of electricity that can be generated by thermal power plant 'i' at time 't' in MWh, $MaxGeneration(RES)_{i,t}$ is the maximum amount of electricity that can be generated by power plant 'i' at time 't' using renewable fuel in MWh and $RESAvailibility_t$ is the availability of renewable energy source (e.g. wind speed or solar irradiance) at any given hour of the year in %.

A flow chart of the market clearing optimization algorithm is offered in Appendix C.

CO_2 emissions: for a given CO_2 emissions cap (tonneCO_2/year), the power generation from all CO_2 emitting plants is constrained until they have emitted an amount that is less than or equal to the emissions cap. The CO_2 emissions (in tonCO_2) from all thermal plants for all hours of the year is summed up and the constraint below restricts total emissions within the cap:

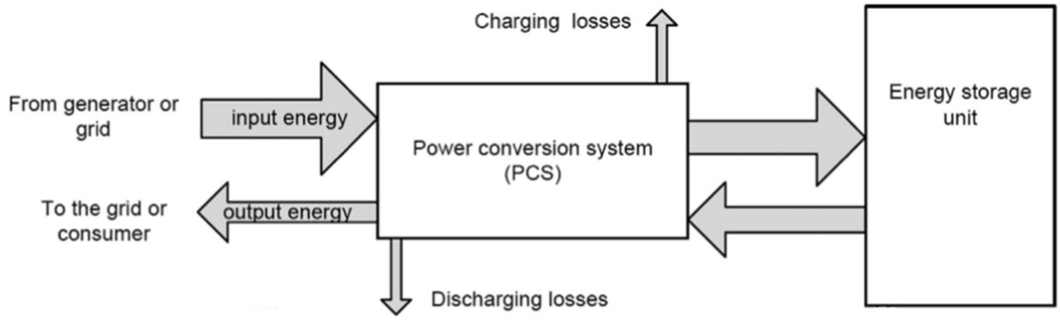

Fig. 3. Main components of EES. .
Adapted from [70]

$$\sum_{i}^{n}\sum_{t}^{n} PPYearlyEmissions_{i,t} \leqslant CO2Cap_{year} \tag{6}$$

The dual value of the constraint in Eq. (6) provides the CO_2 price (€/tonCO_2). The agents make payments according to their annual CO_2 emissions to the national government.

2.4. DR implementation and operation

An overview of different categories of DR programs along with time scales and decision mechanisms for shifting/curtailing demand is given in Appendix B. We have chosen a combination of DR programs of 'demand bidding' and 'time-of-use' which is also implemented as 'permanent load shifting' [131]. The consumers are incentivized to shift demand to off-peak hours where the market prices are lowest. DR is implemented using the principle of cost minimization and medium-term load shift based on intraday and day ahead market trading [3,23,62–63,132]. The reason for shifting demand and not curtailing it is due to the fact that demand is inelastic in the short term (e.g. 24 h or more), therefore, demand is more likely to be shifted rather than curtailed [133]. The objective of DR is to increase the viability of load shifting due to price arbitrage, decreasing consumer costs.

Elastic demand can be shifted within a length of time '*l*' (which is 24 h for this work) given the overall amount of elastic demand to be shifted within '*l*' is provided in the market clearing. The elastic demand variables are set such that the consumption is optimized according to electricity price and the given load is consumed within '*l*'. Eqs. (7) and (8) describe the limits and constraints for shifting elastic demand:

$$0 \leqslant ElasticDemand_t \quad \forall\, t \tag{7}$$

$$\sum_{t=(d-1)*l+1}^{d*L} (ElasticDemand_t) = MaxConsumptionPerPeriod_d \quad \forall\, l = 24 \tag{8}$$

where 'd' = 1, 2, …, N_d and 'N_d' = 8760/l.

Where $ElasticDemand_t$ is the elastic demand that is shifted within '*l*' in MWh and $MaxConsumptionPerPeriod_d$ is the total amount of elastic demand that needs to be shifted within '*l*' in MWh.

A market design option is to include DR in the CM by reducing the level of capacity obligation [123] or, in advanced types of CRMs, there may be efficient ways of stimulating DR.

A reason for allowing DR to bid in the CM is when it bids at a price higher than the market cap. This is the case in PJM RPM, where the system operator contracts DR only to be called in emergencies [134]. The share of DR participation in CMs is significantly decreasing as it mainly has summer capability [135]. In addition, the share of DR in the upcoming PJM RPM auction is projected to be too insignificant to have an impact on the market clearing price [135]. A key issue with participation of DR resources in CMs is the difficulty of establishing a baseline for (aggregated) residential consumers. Even if a reference baseline is set, the consumers may conform to the new pattern of consumption and continue to be remunerated by the CM. If aggregated small-scale consumers (e.g. electric vehicle owners) are allotted capacity credits, they could create peak load periods artificially and then curtail power in order to be remunerated by the CM.

Incentivizing DR in both the electricity and capacity markets could increase consumer costs. DR participating in CM could bid at prices close to value of lost load (VoLL) and the load could eventually end up shifting to off-peak hours rather than being curtailed. However in our model, DR is implicitly included in the electricity market because it leads to lower capacity requirements. For these reasons, while we did not model DR participation in the CM, we are considering this as a question for our follow-up work.

2.5. EES implementation and operation

EES is implemented using the principle of cost minimization based on Wood and Wollenburg [136] for participation in electricity market [70,137]. Fig. 3 describes the main components of EES modelled:

Energy content, power inflow and power outflow for EES are constrained. The cost minimization algorithm optimally charges and discharges it. EES unit starts the year with a certain state of charge (*InitialStateOfCharge*) and is constrained to end the year with a certain remaining charge (*FinalStateOfCharge*). Following are the constraints and limits applied to the operations of EES for market clearing:

$$\begin{aligned} StateofChargeInStorage_t = {} & \left(-\frac{1}{\eta}\right)*StorageDischarging_t \\ & + (\eta)*StorageCharging_t \\ & + StateofChargeInStorage_{t-1} \quad \forall\, t \end{aligned} \tag{9}$$

$$MinStorageInFlow_t \leqslant StorageCharging_t \leqslant MaxStorageInFlow_t \quad \forall\, t \tag{10}$$

$$MinStorageOutFlow_t \leqslant StorageDischarging_t \leqslant MaxStorageOutFlow_t \quad \forall\, t \tag{11}$$

$$\begin{aligned} MinStorageEnergyContent_t \leqslant StateofChargeInStorage_t \leqslant \\ MaxStorageEnergyContent_t \quad \forall\, t \end{aligned} \tag{12}$$

$$StateofChargeinStorage_{t=1} = InitialStateOfCharge \quad \forall\, t \tag{13}$$

$$StateofChargeinStorage_{t=8760} = FinalStateOfCharge \quad \forall\, t \tag{14}$$

where $MinStorageInFlow_t$ is the minimum amount of power that can flow into the EES per hour in MW, $MaxStorageInFlow_t$ is the maximum amount of power that can flow into the EES per hour in MW, $MinStorageOutFlow_t$ is the minimum amount of power that can flow out of the EES per hour in MW, $MaxStorageOutFlow_t$ is the maximum amount of power that can flow out of the EES per hour in MW, $StateofChargeInStorage_t$ is the amount of energy in the EES per hour in MWh, $MinStorageEnergyContent_t$ is the minimum amount of energy that the EES can hold per hour in MWh, $MaxStorageEnergyContent_t$ is the maximum amount of energy content that the EES can hold per hour in MWh and 'η' is the efficiency of EES. The relationship between the power and energy capacity of the EES is as follows:

$$\frac{MaxStorageEnergyContent_t}{MaxStorageOutFlow_t} = DischargeTime \quad \forall\ t \tag{15}$$

where *DischargeTime* is the total discharging time of EES in hours.

EES is also enabled to participate in the CM. The capacity that EES can bid into the CM is $MaxStorageOutFlow_t$. This assumption holds valid considering the day time peak storage discharging and subsequent night time off-peak storage charging. Since EES is not allowed to participate in European or others CMs, there is no set of rules that can serve as an example. Therefore, the bidding behaviour of the EES unit in the CM is kept simple. The price at which the EES capacity is bid in the CM is zero, which means that EES is a price taker in CM clearing. The rules for bidding EES in CM are hypothetical and are subject to experimentation.

2.6. CM clearing algorithm

A year-ahead forward CM has been implemented based on the CM (ICAP) implemented by the New York ISO in the US [54,107,138]. All agents with controllable thermal and intermittent RES power plants can participate in the CM depending on their average availability during the peak load hours. Since every agent owns multiple RES power plants, the phenomenon of aggregate bidding is applied, which is currently implemented in the PJM market in the US [3].

Annual peak load is forecast based on the data from previous year. A reserve margin is added to the expected level of peak load [3]. Upper and lower margins are used to create a sloping demand curve, in which the upper margin is added to and lower margin is subtracted from the expected peak load. The market is cleared between the values representing the sloping demand curve depending on the total capacity bid, the bidding prices and the Cost of new entry (CONE) as shown in Fig. 5. The CONE is defined as the highest price that the producers can bid their power plant's generation capacity at [3]. Fig. 4 describes a stylized CM clearing flow diagram of a year in the model.

Agents bid their power plants' average available capacity; the bid price of a plant is based on expected revenues from the electricity market in the current year and the fixed operating cost of the power plant. If the plant is expected to make a loss, then the bidding price is the loss/MW. If the power plant is expecting to make a profit, then the bid price is zero. Power plants using RES always bid at zero as that is their marginal cost of generating electricity and they are formulated to be price takers. The agents do not strategically bid at higher prices as they are assumed to be price takers. Market power is not modelled. However, if the market is tight, the market price automatically rises due

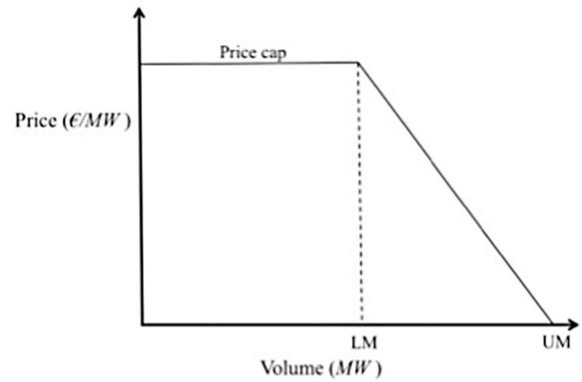

Fig. 5. Sloping demand curve used for clearing the CM with upper margin and lower margin from [166].

to the sloping demand curve. If the capacity does not adequately meet demand and there is a shortage, the clearing price is set at the CONE. This would trigger investment in generation capacity as the agents will be projected to receiver higher CM price. Fig. 5 shows the sloping demand curve used for CM clearing.

If there is a surplus of capacity in the market, all bids above the CONE are automatically rejected and bids under the CONE are accepted. If there is a shortage of capacity, all bids under the CONE are accepted and the CM clearing price is set at CONE.

A more detailed version of the CM clearing algorithm can be found in [38].

2.7. Investment in generation capacity by private investors

The investment algorithm is explained comprehensively in Richstein [111], and is summarized here, along with the structural changes made to the algorithm. An extrapolated load duration curve is constructed from the hourly market clearing data. The same goes for the supply curve, which includes the expected power plants to be operational by the future year.

The agents then estimate expected demand, fuel prices and CO_2 price in a future reference year. These predictions are made using geometric regression looking at past market data. The agents then consider expected electricity prices, which are computed by comparing estimations of the expected merit order and expected demand in the future reference year. With this information, the agents make sub-optimal investment decisions as per the imperfect foresight they have (see Fig. 6) [139].

The first agent to make an investment decision reviews all the

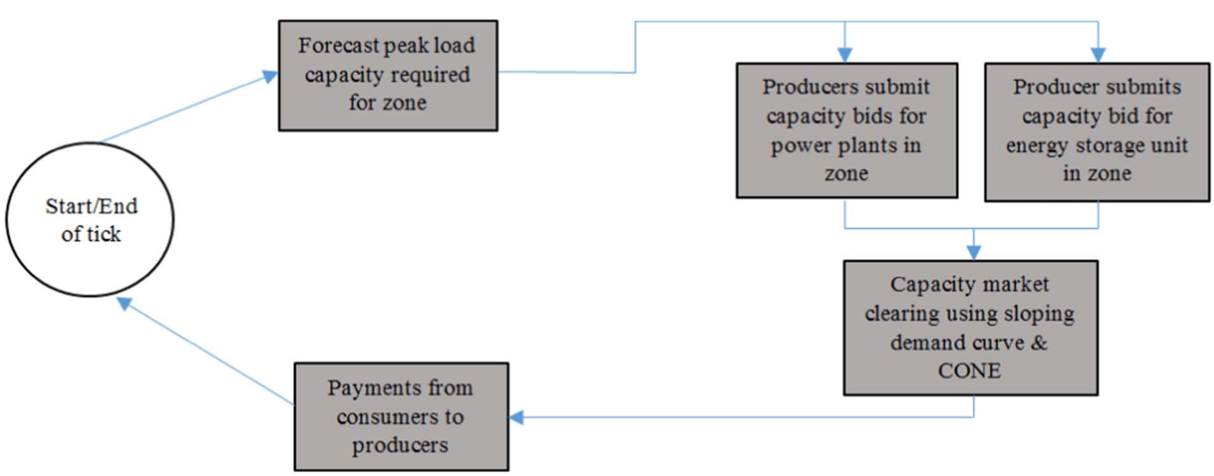

Fig. 4. Stylized CM clearing flow diagram of a year in the model.

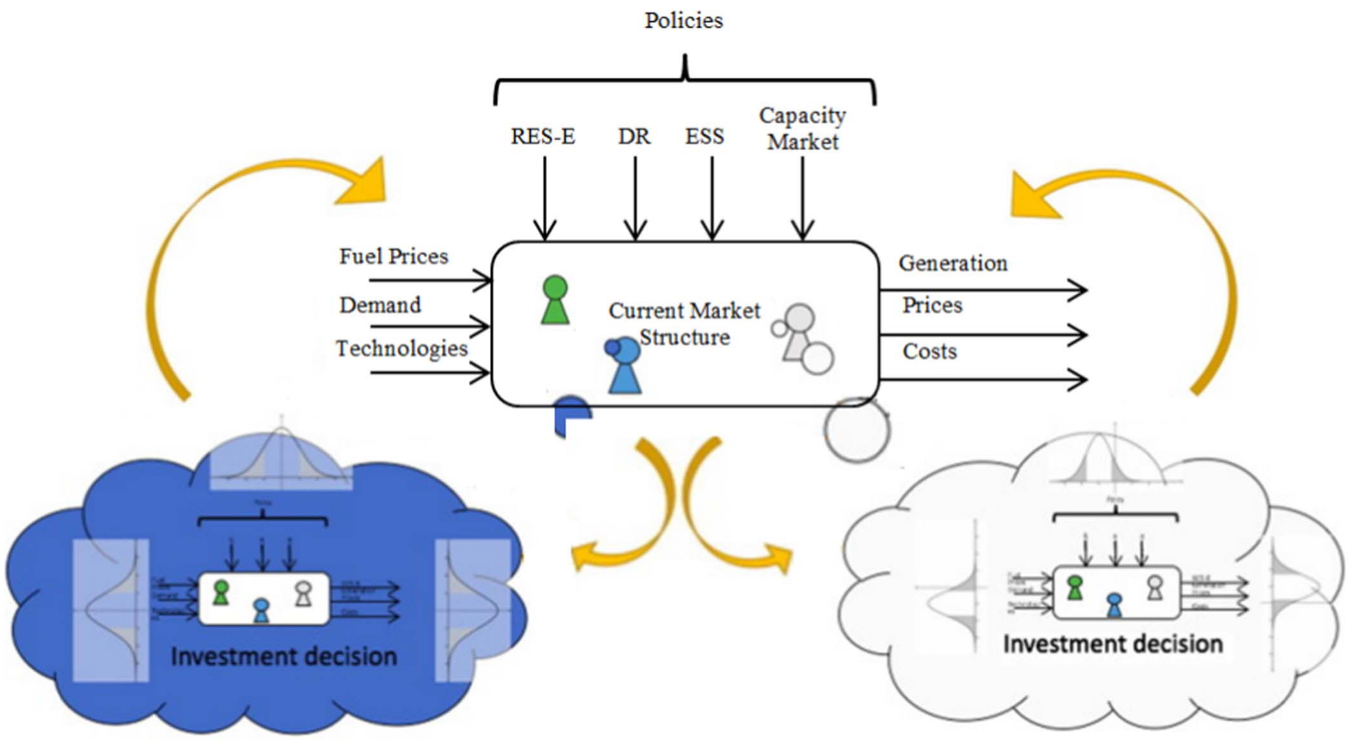

Fig. 6. Investment behaviour of agents and interaction with market environment in EMLab-Generation. Adapted from [111].

available power generation technologies and invests in a power plant with the technology that gives the highest return on investment (*RoI*), if there is a positive business case. Then the subsequent agents repeat the procedure until there is no positive business case for any new power plants. An agent can only invest in one power plant during an iteration in order to give other agents a fair chance. All agents start the simulation with equal cash. They do not have a fix budget but they cannot invest if the cash they have is less than what they need in order to invest. The agents are chosen randomly primarily to give all agents a fair chance when it comes to making investments in new plants. We follow this reasoning because the first agent to make an investment impacts the investments decisions of the following agents. All agents will have the knowledge about the investments made by the agents preceding them. So if the agents are chosen in the same order and not randomly to make investment decisions, the first agent would always have an unfair advantage over the agents following it. The agents will keep building power plants as long as there is a business case for them in the reference year.

An effect of imperfect foresight of the agents is an investment cycle. Since the agents extrapolate the current information and past market data, this leads to periodic over-estimation and under-estimation of future electricity demand. The agents therefore over-invest or under-invest in generation capacity. This feature is modelled intentionally, since we wanted to create an investment cycle to analyse the performance of the CM. If the investment behaviour of the agents is optimal, it is difficult to analyse the robustness of policy instruments like CMs [140]. This enables us to model more realistic investment behaviour of the agents as compared to optimal decision making.

For this work, the agents look 7 years ahead from the current year and use the market data from the past 5 years to make forecasts. The agents look 7 years ahead from the current year in order to accommodate the time needed for constructing a power plant. Within 7 years all power plants that are in the pipeline to be constructed are operational and ready to become a part of the supply mix. The agents use market data from the past 5 years in order to respond to the near past trends as well as to have adequate information to make reasonable assessments. If the agents choose to look back for a longer period of time, then they would lose their ability to respond to short-term trend change.

The investment module enables the private energy producing companies to invest in power plants with intermittent renewable technologies as well. Since RES technology targets are given as an input, private investors can only invest in RES-E till technology target is reached.

As the agents iterate over all the available power generation technologies, they calculate the *RoI* for each technology. The *RoI* is calculated by the cash inflows and cash outflows for every power generating technology:

$$CInflow_{Op,g} = \sum_{s} (ElectricityPrice_{s,t+n} * RunningHours_{s,g,t+n} * AvailableCapacity_{g,s}) + CMRev_g \tag{16}$$

$$COutflow_{(VC+FC)Op,g} = \sum_{s} (VariableCost_{g,t+n} * RunningHours_{s,g,t+n} * AvailableCapacity_{g,s}) + FixedCost_{g,t+n} \tag{17}$$

For ‘s’ = 1, 2, …, 20.

where $CInflow_{Op,g}$ are the total cash inflow for an operational power plant ‘g’; $ElectricityPrice_{s,t+n}$ is the expected market electricity price for segment ‘s’ estimated at time ‘$t+n$’ where ‘t’ represents the current year and ‘n’ represents a future year; $RunningHours_{s,g,t+n}$ are the total number of hours for which is the power plant ‘g’ is supplying in the segment ‘s’ at time ‘$t+n$’; $AvailableCapacity_{g,s}$ is the total available capacity of the power plant ‘g’ in segment ‘s’; $CMRev_g$ is the revenue the power plant ‘g’ is expected to make in ‘$t+n$’; $COutflow_{(VC+FC)\ Op,g}$ are the cash outflows for an operating power plant ‘g’ including the variable fuel costs and fixed operating costs only; $VariableCost_{g,t+n}$ is the variable fuel costs of the power plant ‘g’ at time ‘$t+n$’ and $FixedCost_{g,t+n}$ is the fixed operating cost of the power plant ‘g’ at time ‘$t+n$’.

The ‘Weighted Average Cost of Capital’ or *WACC* is used as a discount rate in order to discount the future cash flows.

$$WACC = ((1--r_D)*I_E) + (r_D*I_L) \tag{18}$$

where is r_D is the debt ratio of investment set at 0.7 as the debt equity ratio is set at 70:30, I_E is the equity interest rate set at 12% and I_L is the load interest rate set at 9%. Therefore, a discount rate or WACC of 10% (based on IEA [141]) for investment in competitive unbundled electricity markets is used in order to discount the future cash flows.

$$DscCInflow_g = \sum_t CInflow_{Op,g}/(1 + WACC)^t \tag{19}$$

$$DscCOutflow_g = \left[\sum_t COutflow_{(VC+FC)Op,g}/(1 + WACC)^t\right] + \left[\sum_{t_1} InvestmentCost_g/(1 + WACC)^{t_1}\right] \tag{20}$$

For 't_1' = 0, 1, …, t_b and 't' = t_b + 1, …, t_b + t_D

where $DscCInflow_g$ are the discounted cash inflows for power plant 'g'; $DscCOutflow_g$ are the discounted cash outflows for the power plant 'g'; $InvestmentCost_g$ is the total investment cost for the power plant 'g'; 't' represents the time steps in years; t_b is the time it takes to construct the power plant and t_D is the depreciation time of the power plant. The RoI for power plant 'g' or RoI_g is calculated using Eq. (21):

$$RoI_g = (DscCInflow_g - DscCOutflow_g)/DscCOutflow_g \tag{21}$$

The agent will finally invest in the power plant using the power generation technology with the highest value of RoI_g.

2.8. Investment in renewable generation by government investors

Since European governments are subsidizing RES-E, renewable policy is implemented in the model by assuming that the governments exogenously fulfil policy targets. These are implemented as national renewable target investors who only invest in RES-E if private investment does not fulfil the government targets.

2.9. Investment in EES

The investment role for EES is designed to observe the profit or loss incurred in the past year and optimize its capacity for the future year. The process is as follows:

1. The total revenues of EES from the electricity market and CM are calculated from the past year.
2. The total fixed operating and investment costs of EES for the past year are calculated.
   a. If the total revenue from the EES from electricity and capacity market (if included) is higher than its total amortized fixed operating cost, and its capacity is greater than 10% of the peak load in the electricity market, then its energy storage, power discharging and power charging capacity is increased at most by 5%. Otherwise it is increased by 15% at most. This limit is imposed in order to keep the EES capacity growth within reasonable range.
   b. If the total revenue from the EES is less than its total fixed operating costs, then its energy storage, power discharging and power charging capacity is decreased at most by 5%. If EES is incurring considerably higher cost then its profit, and the capacity of EES unit is less than 4% of peak load in the electricity market, then its capacity is not reduced, to keep a minimum volume of EES in the market.
3. The agent that owns the EES unit makes payment for the increased capacity, if that is the case.

2.10. Dismantling power plants

The criteria for dismantling power plants owned by private agents and by government subsidized agent differ. Power plants owned by subsidized agents are dismantled when they reach the end of their technical life time as the plants are only provided subsidies until then. Power plants owned by private investors are dismantled depending on their profitability in the past 5 years and their expected profits in the coming year. Profitability is calculated as the ratio of profits divided by the investment cost of the power plant. The expected revenues from both electricity market and CM are estimated. Power plants cannot be dismantled unless sufficient information from the past years is available to make an appropriate dismantling decision. The expected revenues of the power plants in both electricity and capacity market in the future year are calculated by using past observed demand data, namely the load duration curve, which is extrapolated in order to make a forecast for the demand and capacity obligations in the future year. The operating cost of power plants increases as they age beyond their technical lifetime. This results in a decrease in their profitability and they become economically unviable. A more detailed version of the dismantling algorithm is described in Bhagwat [107].

2.11. Payment of dividends

Like other corporations, agents have to distribute a portion of their net profits among shareholders. For this purpose, an agent "shareholder" has introduced for each agent. RoI [142] to be shared with the shareholders is typically decided by the board of executives. We make a simplifying assumption that if the RoI of an agent is greater than 20% [143], then 70% of the net profit is transferred to shareholder. The remaining 30% is retained by the company in order to make future investments.

2.12. Input data: Dutch electricity market

For this paper, we consider an uncongested isolated power system similar to the one in the Netherlands. Six power producing companies are included in the market. One of these companies only owns the EES unit and no power plants, if EES has been included in the experiment. The time series load data for the Dutch electricity market is taken from ENTSO-E for the year 2016. The load data is divided in two parts: 92% of the load is inelastic and 8% of the load is elastic. The inelastic load is input on an hourly basis whereas the elastic load is aggregated every 24 h and input on a daily basis. The amount of overall elastic load (8%) is taken from the minimum possible share of load reduction potential, the most conservative estimate of demand elasticity in the Netherlands [58]. Elastic demand is shifted within a deadline of 24 h and is input per day based on intraday and day-ahead market trading [3,23,62–63,132].

For EES, the technology considered is pumped hydro storage (PHS). We chose PHS from the various technologies for EES by comparing technical characteristics. PHS is chosen on the basis of higher response time, higher discharge time, maximum cycles per year and optimal costs, suitable for this work [70] where short periods of wind and solar droughts are studied, that can last for several hours. The initial costs (capital and operational) are given in Table D.3, whereas the charging time, discharging time and 'η' is given in Table D.4 [70]. The *InitialStateOfCharge* and *FinalStateOfCharge* are both set at 50% of the total storage capacity of the EES. The capital and operational cost learning curves for PHS are based on conservative estimates from IRENA [144], IEA [145] and Jaffe & Adamson [146]. The initial supply portfolio for the Netherlands is taken from ENTSO-E for the year 2016. The targets for development of RES-E generation in the Netherlands by the year 2050 are based on national renewable energy action plan [147]. The fuel prices are based on BP Global [148], IEA [149], DECC [150] & estimates by Faaij [151]. Electricity demand growth and fuel prices are modelled as stochastic trends, by creating triangular distributions [152] to determine the year-on-year growth rate and capture the effect of uncertainty in the market. The average electricity demand growth trends are taken from EEA [153], European Commission [154] and EIA [155] by observing the past and estimated future trends. The assumptions for the average growth rate, upper and lower bounds of the stochastic functions are summarized in Table D.2 [5,107,110].

The assumptions for power generation technologies are given in Table D.1. The fixed costs for the power generation technologies and costs learning curves are based on IEA [156]. The agents use a discount rate of 10% (based on IEA [141] when investing in new power plants. Hourly RES availability is based on the data from ENTSO-E for the year 2016 and Hirth [157] which uses ERA weather data. VoLL of 11 k €/MWh is used based on European Commission [158] and De Nooij et al. [159]. Carbon emissions from the Dutch electricity sector and the emissions reduction goal for 2050 are based on European Commission [160] and EC [161]. For the CM, CONE of 120 k € is used along with an upper and lower margin of 2.5% for the sloping demand curve, based on Newell et al. [162], PJM [3]. A reserve margin of 8% is set for the CM based on Moghanjooghi [113]. The model runs for 40 ticks with each tick representing a year, starting from the year 2016.

2.13. Output data analysis

Since the model has multiple stochastic parameters, we performed data analysis by simulating each experiment multiple times in order to make significant conclusions by looking at the range of the output parameters. Multiple repetitions of the experiments are required because the agents are randomly chosen to invest in new power plants and many parameters (e.g. demand growth rate and fuel prices) are stochastic. We run 40 scenarios for the same realization of each experiment with different fuel prices and demand growth trends (described in the Section 3) in order to avoid random differences between the results, based on Iychettira et al. [110] and van Dam et al. [163]. All results from all the experiments are included in the data analysis. No data from any of the scenarios of any experiment is excluded. The final results are presented by calculating the mean, 50% envelope and 90% envelope of the output data. This approach helps us analyse the effect of uncertain parameters on the model by observing their average and range.

3. Experiment design

We have designed six experiments in order to study the impact of flexibility options upon CM, including the choice whether to remunerate EES in the CM. The experiments are designed to enable us to study all possible combinations of policy instruments for security of supply and DSM. See Table 1.

The first experiment is the base case, which is an energy-only market without CM, DR and EES. The second experiment includes DR and EES but no CM is implemented, in order to observe the effect of these flexibility options on the market. The third experiment does not include DR and EES but has a CM, in order to observe its effect in a worst case scenario, i.e. a scenario without flexibility options. The fourth and fifth experiments include DR and EES as well as a CM. The difference is that in the fourth experiment, EES is not participating in the CM, while in the fifth experiment, it is. The sixth experiment does not include DR but only EES in combination with a CM (with EES bidding). Generation from RES develops according to the national targets is all experiments.

Table 1
Experiments design – naming convention.

Sr. No.	Experiment name	CM	DR	EES
1.	P1Scen1	×	×	×
2.	P1Scen2	×	✓	✓
3.	P1Scen3	✓	×	×
4.	P1Scen4	✓ (Without EES bid)	✓	✓
5.	P1Scen5	✓ (With EES bid)	✓	✓
6.	P1Scen6	✓ (With EES bid)	×	✓

4. Model limitations and assumptions

The model enables the participation of one DR program per electricity market. Similarly one EES unit per electricity market is allowed to participate in the spot market and CM. Incorporating multiple DR programs and EES exponentially increases the computational time of the model and is out of the scope of this research. The agents are not enabled to exercise any market power. All the operational power generators always bid there full capacity at marginal costs.

In this paper, we studied a closed power market without any interconnectivity with neighbouring markets. If interconnections are taken into consideration, the impact of DR and EES cannot be accurately analysed due to leakage of benefits of the CM and EES to the interconnected markets. In future, we plan to study the impacts of DR and EES on system adequacy and cross-border effects in regional markets.

The EES investment algorithm does not calculate and invest on the basis of *RoI* for EES technology, similar to the investment role for generation capacity, because it was too complex to forecast future expected revenues for EES. The *RoI* of EES technology could only be calculated by clearing the electricity market on an hourly basis in a future year with the proposed EES. Clearing a future market multiple times with an hourly granularity presented too large a computational time requirement.

Ramping constraints and unforeseen shutdowns of power plants are ignored [164], because the objective of this research is to study the long-term evolution of the system. Including ramping constraints also presents a computational bottleneck. Intra-zonal grid constraints are also ignored since they are out of the scope of this research. The electricity market is cleared on an hourly basis since the impact of sub-hourly modelling in power systems is negligible as compared to hourly modelling [165]. A central assumption is that the agents calculate the *RoI* for a power plant by including it in the supply curve for a market clearing in a future year. The revenues from this future market are then extrapolated for the entire life of the power plant. These revenues are likely to be above or below expectations due to imperfect foresight. This enables us to simulate realistic forecasting errors made by agents in order to have realistic observations for studying policy instruments.

The findings of this research apply to electricity markets (competitive and unbundled) with a centralized CM along with a limited share of DR and medium-term EES (with a discharge time of 24 h or more). These markets are assumed to have a diverse supply portfolio including thermal power generation technologies and RES-E, which is the case for European and North American electricity markets. Agents with market power or a monopolist would behave differently in the context of work presented and thus the results would differ.

5. Results and analysis

5.1. Model outcomes

The following performance indicators are used to analyse the performance of the system:

(1) Number of hours per year when there is a shortage in the electricity market.
(2) Volume of lost load (MWh/year) during a shortage in the electricity market.
(3) Annual average electricity price (Euro/MWh).
(4) Capacity obligation for the CM (MW/year)
(5) CM clearing volume (MW/year)
(6) Annual CM clearing price in €/MW
(7) Total available non-intermittent power generation capacity (MW) (the available capacity of intermittent RES power plants is not

included) and the residual load (load served by intermittent power generation capacity is not included) during the peak hour (MW) per year is used to calculate the residual supply ratio:

$$\text{Residual Supply Ratio} = \text{Total available non-intermittent generation capacity(MW)} / \text{Residual Peak Load(MW)}$$

(8) Total cost incurred by consumers over 40 years (Euro):

$$\text{Total consumer cost} = \text{Cost of Electricity} + \text{Cost of CM} + \text{Cost of RES Policy} + \text{Cost of lost load}$$

(9) Number of EES discharging cycles per year
(10) Change in EES capacity per year (indication of investment in EES)
(11) Volume of elastic load (MWh/year)

Some of these performance indicators are correlated. Shortages increase electricity prices and therefore consumer cost (as consumers pay electricity prices equal to VoLL), decrease bids to the CM (since the power plants will be projected to have more revenues as compared to operating costs) and increase EES investment as there is more opportunity for price arbitrage between peak and off-peak hours during shortages. Shortages maximize the deployment of elastic load to shift from peak (where prices are set at VoLL) to off-peak hours. Higher CM clearing prices also lead to an increase in the consumer cost as the CM clearing price is equal to CONE if the supply to the CM is not able to balance demand. This triggers an investment cycle, consequently impacting overall generation capacity and the residual supply ratio.

5.2. Sensitivity analysis

We performed sensitivity analysis on a number of input parameters by increasing their value by 10% in experiments 1, 2 and 3 in order to evaluate their impact on the output. An increase of the VoLL leads to a marginal increase in the electricity price and hence the average consumer cost. Increasing the share of elastic load in the system leads to marginally lower peak load, electricity prices, shortages, consumer cost and capacity obligations for CM. Increasing the volume of EES capacity leads to marginally reduced electricity prices, consumer cost and shortages. Increasing the discount rate makes the agents more risk averse, leading to more shortages. Increasing the share of RES-E reduces electricity prices and the share of thermal plants in the supply mix. Increasing the fuel prices leads to marginal increase in consumer cost. Fig. 7 shows the percentage change in output (given on the horizontal scale) when certain inputs are increased (given on the vertical scale).

5.3. Discussion of results

Experiments 3, 4, 5 and 6 include a CM. The CM is somewhat overdimensioned (as ramp rates and capacity outages are not considered), at least in comparison to the limited swings in demand growth in our experiments (which is the case for Netherlands), which results in low shortages in the electricity market. The average number of hours per year in which shortages are witnessed in experiments 1, 2 and 3 is shown in Fig. 8. The average number of shortage hours for all the simulation runs is 9.5 h/year in experiment 1, 1.8 h/year in experiment 2 (81% lower than in experiment 1), and 0.28 h/year in experiment 3 (97% lower than in experiment 1).

The corresponding annual average volume of lost load in the electricity market is shown in Fig. 9. The annual average volume of lost load for all the simulation runs is 9990.15 MWh/year in experiment 1, 1508.59 MWh/year in experiment 2 (84.9% lower than in experiment 1), and 157.28 MWh/year in experiment 3 (98.4% lower than in experiment 1). Shortages decline significantly when flexibility options or a CM are implemented. No shortages occur in experiment 4, 5 and 6.

The energy-only market without flexibility options (experiment 1) exhibits a high number of shortages because of the myopic behaviour of investors. This corresponds with the findings of Keles et al. [123] and Mercados et al. [99]. The volume of shortages significantly declines when DR and EES are included in an energy-only market (experiment 2). Apparently, even a limited volume of DR and EES improves system adequacy significantly in an energy-only market. DR reduces the peak load by shifting it to off-peak hours, and EES takes advantage of the price arbitrage during peak (discharging) and off-peak (charging) hours, which leads to lower electricity price volatility and fewer shortages. The shortages are further reduced with a CM (experiment 3). No shortages occur in experiments 4, 5 and 6.

The modelled scenarios do not include rare weather events, e.g., weeks of low wind availability, and/or severe dips in temperature during prolonged winters, during which the potential of DR may run out. Long-term EES would be required in order to supply in these cases, but this is currently too expensive (c.f. [70]). More advanced modelling of DR and EES is needed to analyse system adequacy in more depth, including multiple types of flexibility options (DR and EES with different characteristics), and more realistic (less then optimal) operational decisions.

Fig. 10 shows the average annual electricity prices in all the experiments. The electricity prices are decreasing over time with increasing share of RES-E. The average of annual electricity price for all

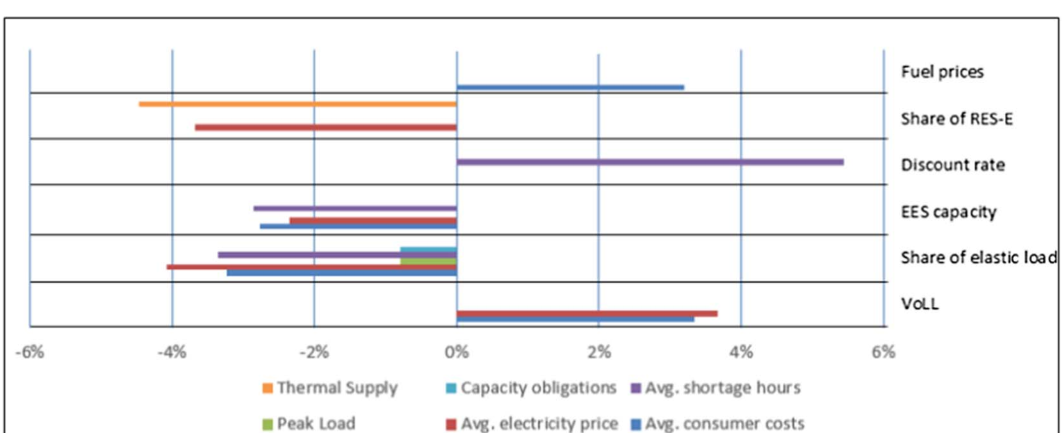

Fig. 7. Sensitivity analysis – % change in output.

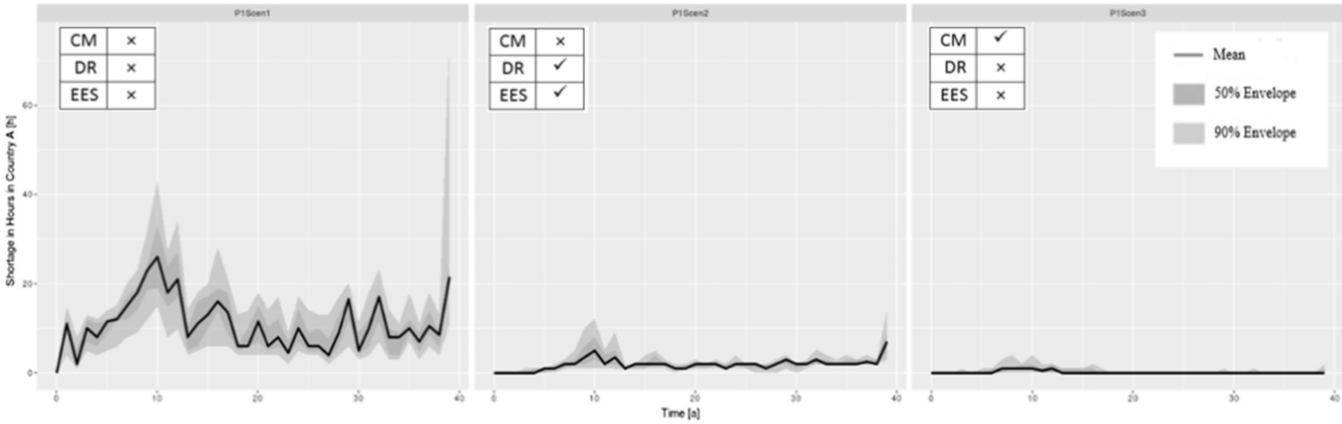

Fig. 8. Annual shortages (average number of hours per year) in experiments 1, 2 & 3 (in that order).

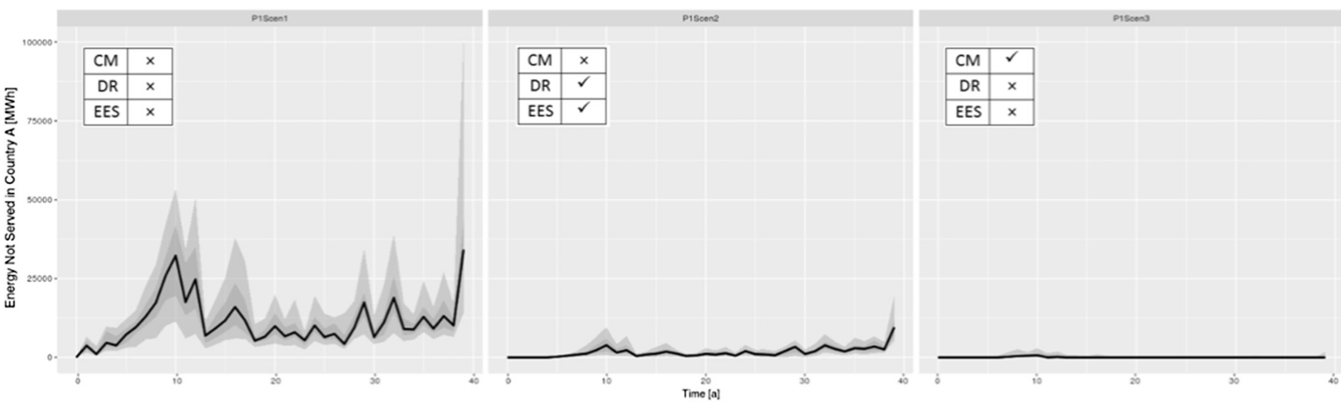

Fig. 9. Annual average volume of lost load [MWh] in experiments 1, 2 & 3 (in that order).

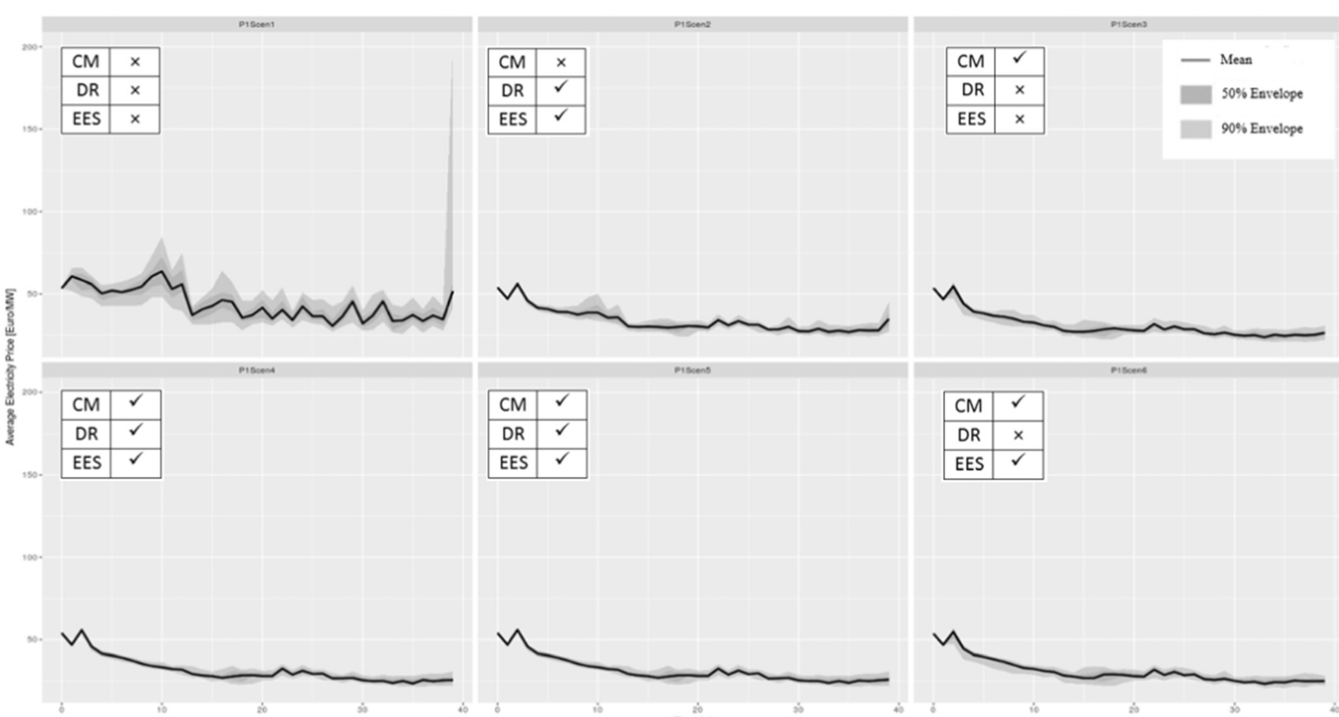

Fig. 10. Average of annual electricity prices in experiments 1, 2, 3, 4, 5 & 6 (in that order).

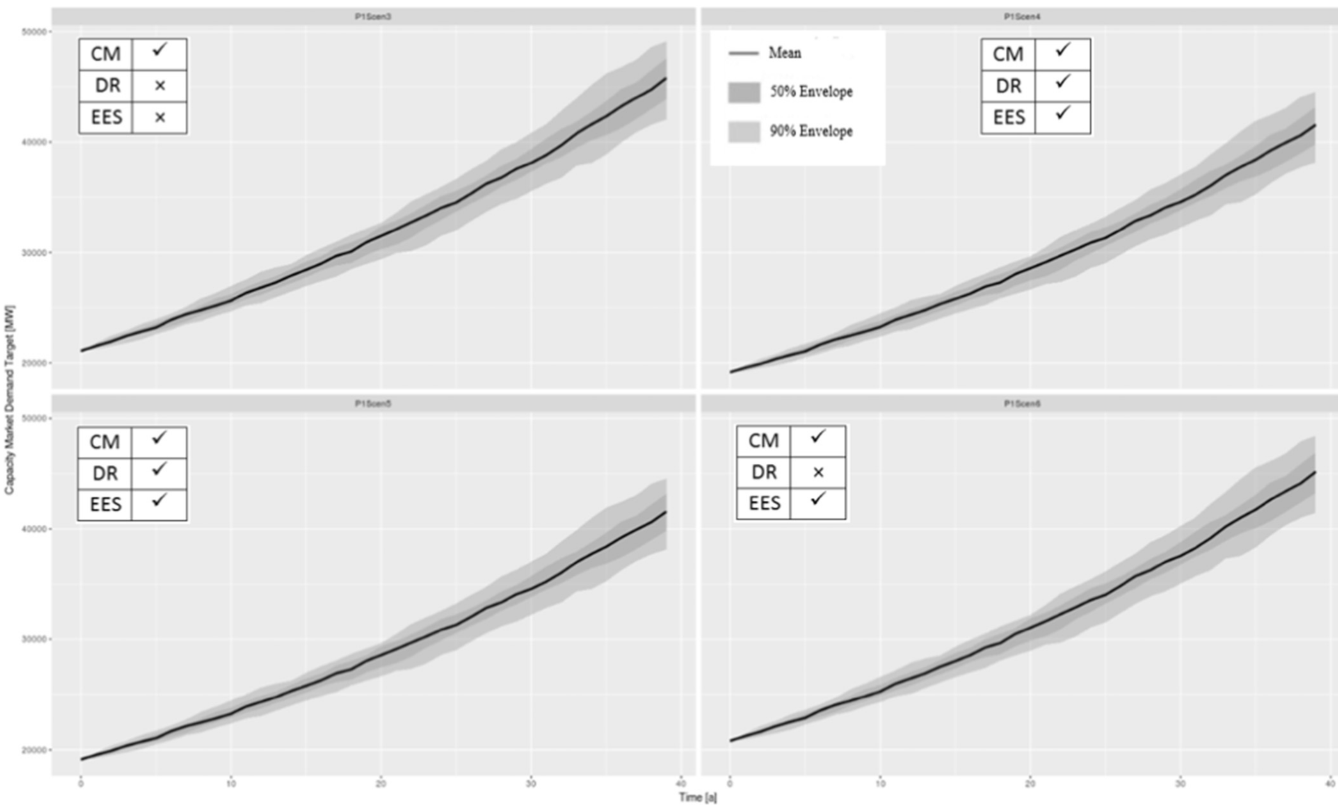

Fig. 11. Annual capacity obligations for CM (MW/year) in experiments 3, 4, 5 & 6 (in that order).

the simulation runs is 44.7 €/MWh in experiment 1. It is 33.9 €/MWh (24.2% lower than in experiment 1), 32.7 €/MWh in experiment 3 (26.8% lower than in experiment 1), 31.6 €/MWh in experiment 4 (29.3% lower than in experiment 1), 31.45 €/MWh in experiment 5 (29.6% lower than in experiment 1), and 32.4 €/MWh in experiment 6 (27.5% lower than in experiment 1).

When determining the capacity obligations (in MW), the regulator adds the reserve margin of 8% to the expected peak load. However, if DR is included, 8% of the peak load (the share of elastic load) in the electricity market is shifted to off-peak hours. Therefore the total capacity obligation, as set by the regulator, are reduced by 8% in experiment 4 and 5 (which include DR), compared to experiment 3 and 6 as shown in Fig. 11.

Since the capacity obligations is reduced by 8% if DR is present in the electricity market, the average CM clearing volume is reduced equally in experiment 4 and 5. Fig. 12 shows the average volume of capacity contracted in the CM.

Fig. 13 shows the yearly CM clearing price. The agents bid their operating loss per MW in the CM if negative revenues are expected. Average CM clearing price for all simulation runs is 27.7 k€/MW in experiment 3. It is 26.7 k€/MW in experiment 4 (3.5% lower than in experiment 4), 26.6 k€/MW in experiment 5 (3.87% lower than in experiment 4), and 27.5 k€/MW in experiment 6 (0.54% lower than in experiment 4). The CM costs are reduced since the market has a lower capacity target as well as a lower clearing price in the presence of DR and EES. The difference between the CM clearing price in experiment 4 and 6 is not significant due to the low amount of capacity bid by the EES in the CM. Since no investment is being made in EES (discussed later), the volume of EES capacity bid into the CM does not change over the years.

Fig. 14 shows the residual supply ratio. EES is not included in the calculation of the residual supply ratio. The initial dip in the residual supply ratio, which is seen in all experiments, is due to the dismantling of existing generation capacity in the Netherlands that is not profitable. The average residual supply ratio for all the simulation runs is 0.96 in experiment 1. It is 0.98 in experiment 2 (2.7% higher than in experiment 1), 1.065 in experiment 3 (9.7% higher than in experiment 1), 1.064 in experiment 4 (9.7% higher than in experiment 1), 1.064 in experiment 5 (9.6% higher than in experiment 1), and 1.065 in experiment 6 (9.7% higher than in experiment 1). The average residual supply ratio in experiment 3, 4, 5 and 6 is approximately 6.45% higher than the required supply, indicating that the CM incentivizes excess supply in our model. The residual supply ratio is higher in an energy-only market with DR and EES (experiment 2) as compared to an energy-only market without flexibility options (experiment 1), as the flexibility options stabilize the market. The 50% and 90% envelopes of data in the figure above show the investment cycles in experiments, a result of the imperfect foresight of the agents that affects their investment decisions.

Fig. 15 shows box plot of total consumer cost over the simulation period of 40 years for all experiments. The average consumer cost for all the simulation runs in experiment 2 is 30.6% lower than in experiment 1. In an energy-only market, DR and EES significantly reduce consumer cost due to the reduction of shortages. The average consumer cost in experiment 3 is 11.1% higher than in experiment 2. Therefore, the introduction of a CM reduces consumer cost significantly: the cost of additional generation capacity is more than offset by the reduction in shortage hours (as was also found by Keles et al. [123]). Since the consumer cost in an energy-only market with flexibility options (experiment 2) is lower than in a system with CM and no flexibility options (experiment 3), as DR and EES improve system adequacy in a similar way (at least in our model), the total volume of generation capacity can be lower as it is more efficiently used. The average consumer cost in experiment 4 and 5 is approximately 4.7% lower than in experiment 3 (cost is almost same due to the negligible impact of EES in the CM). A

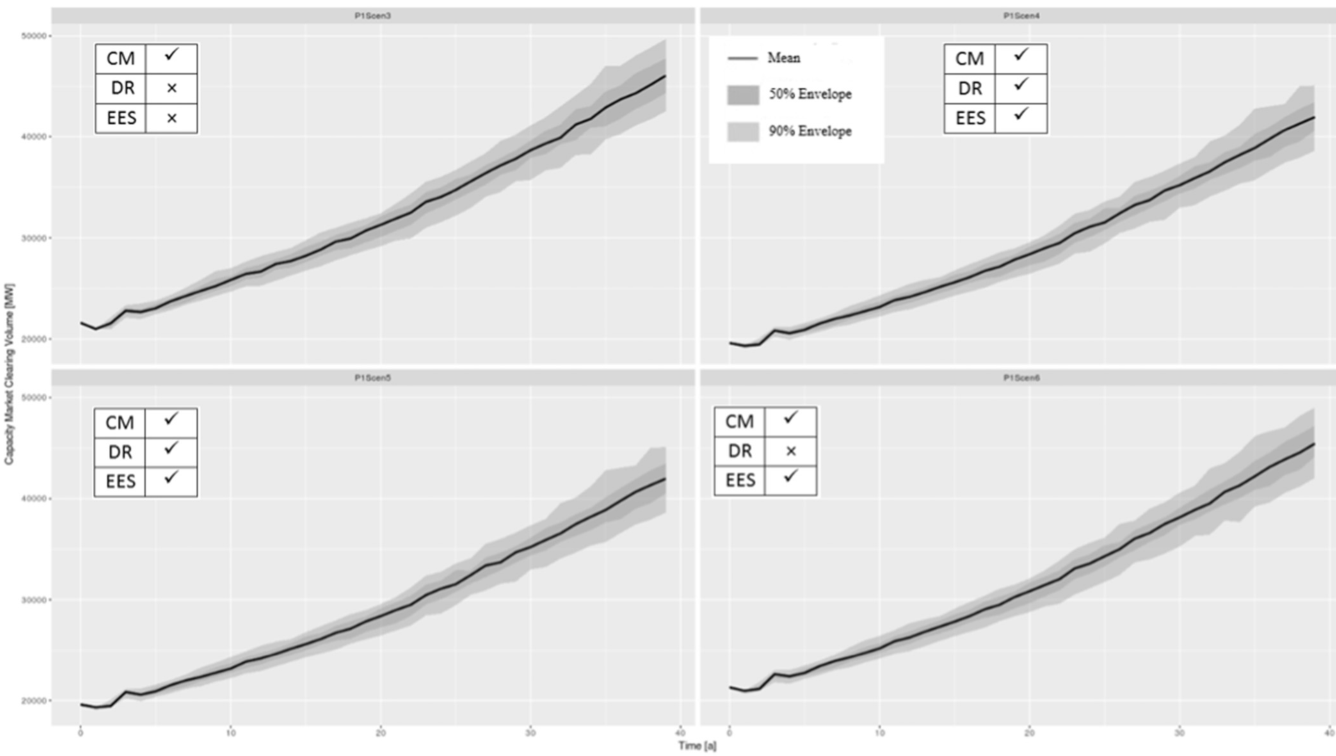

Fig. 12. CM clearing volume (MW/year) in experiments 3, 4, 5 & 6 (in that order).

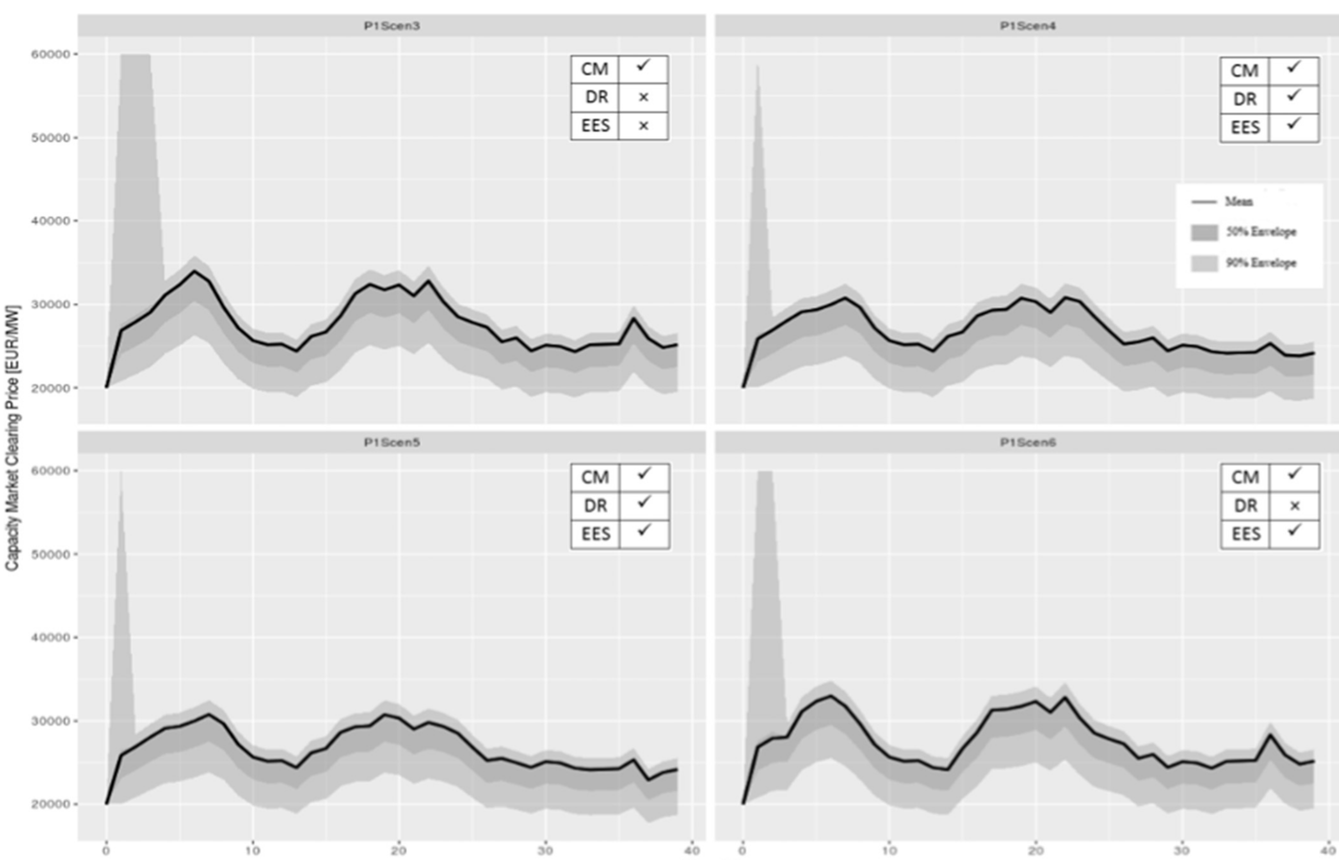

Fig. 13. CM clearing price in €/MW per year in experiments 3, 4, 5 & 6 (in that order).

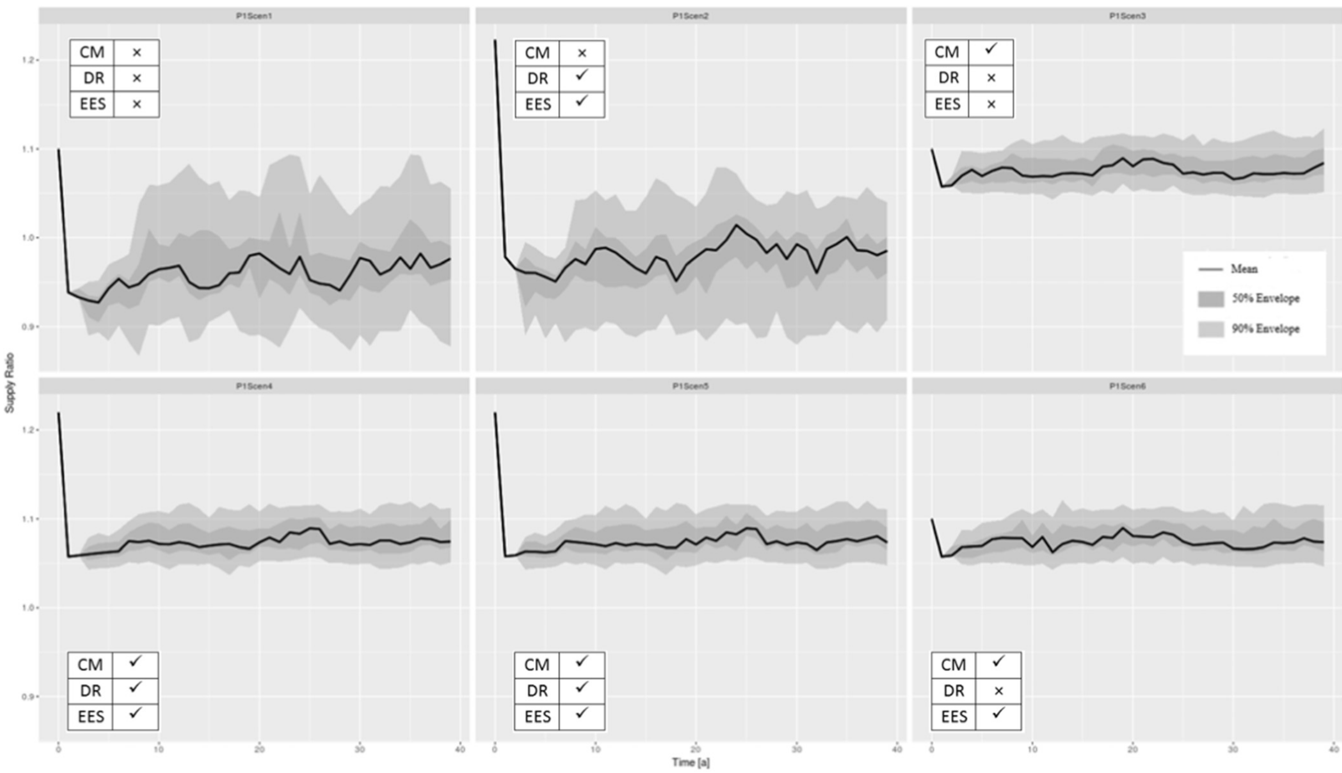

Fig. 14. Residual supply ratio in experiments 1, 2, 3, 4, 5 & 6 (in that order).

CM with DR and EES performs better in terms of cost to consumers than a CM without flexibility options. The average consumer cost in experiment 6 is approximately 3.42% lower than in experiment 3, but 2.25% higher than in experiment 2.

These results indicate that in the presence of DR and EES (experiment 2) the case for a centralized CM is lessened. If the entire cost of EES over its lifetime are added, the average consumer cost in an energy-only market with DR and EES (experiment 2) increases marginally (by 0.05%), remaining approximately 9.6% below the consumer cost in an energy-only market with a CM (experiment 3) and almost

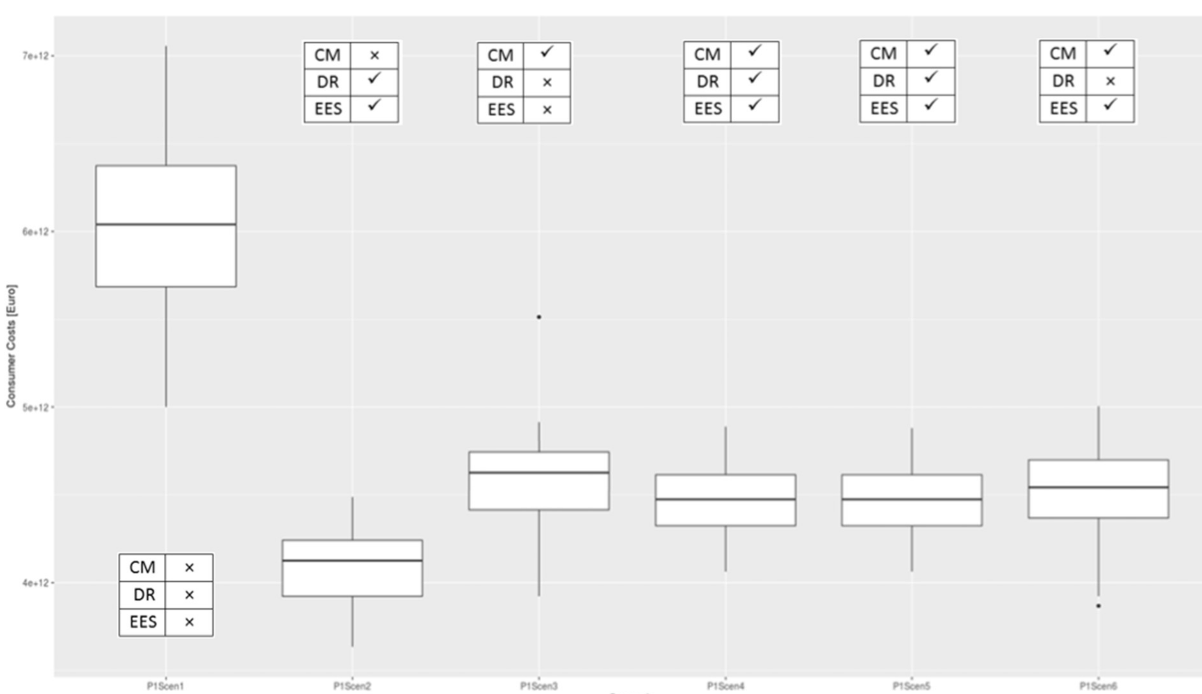

Fig. 15. Total consumer cost (over the entire simulation period – 40 years) in € in experiments 1, 2, 3, 4, 5 & 6 (in that order).

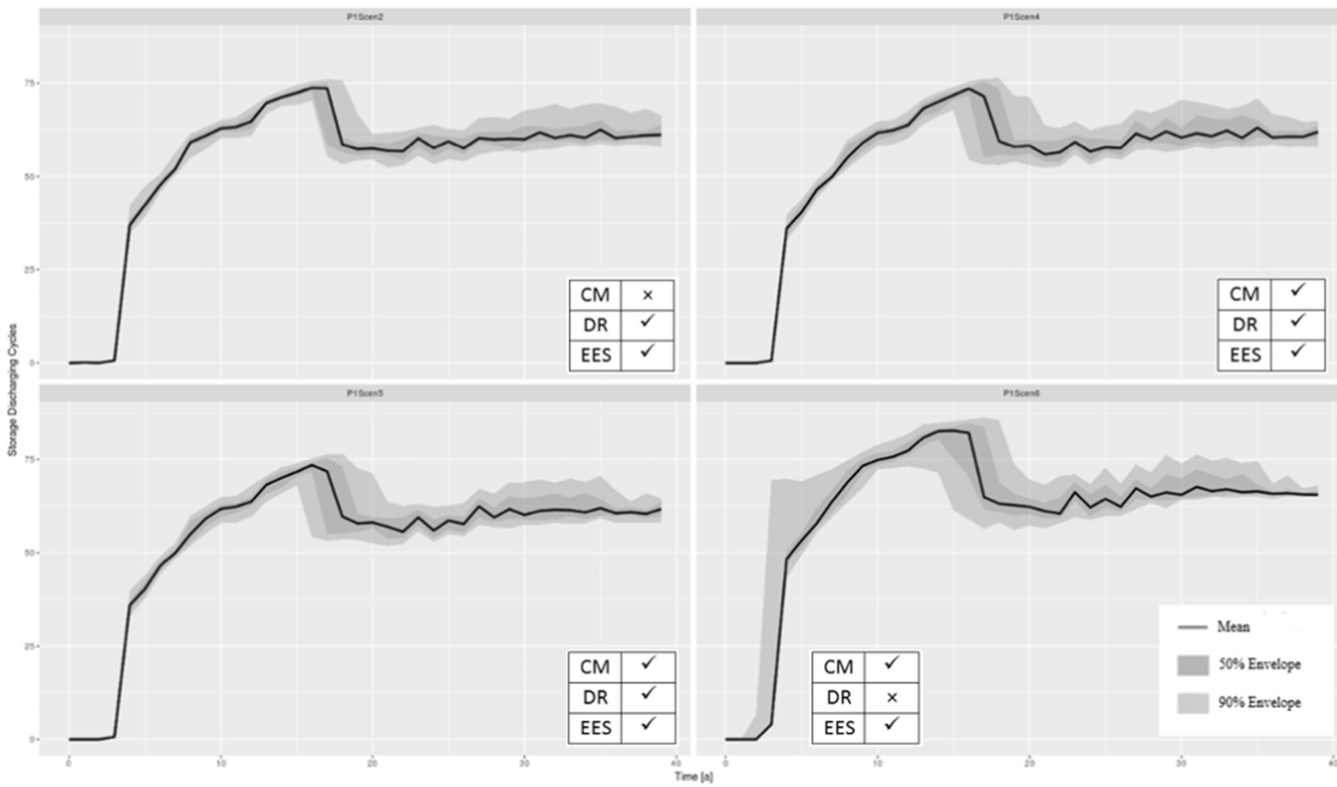

Fig. 16. Number of EES discharging cycles per year in experiments 2, 4, 5 & 6 (in that order).

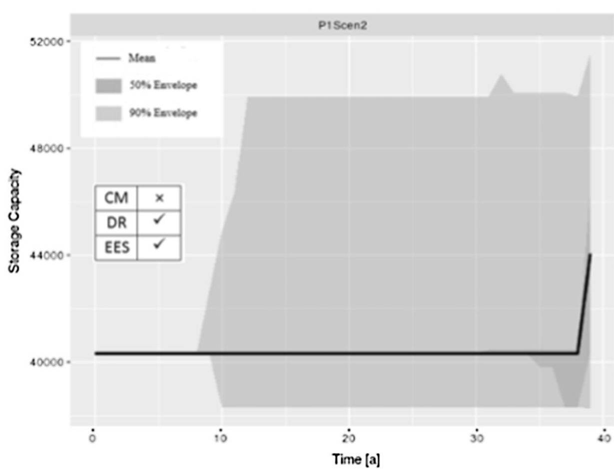

Fig. 17. Change in (investment) EES capacity in experiment 2.

5.1% below the consumer cost in an energy-only market with CM and flexibility options (experiment 4, 5 and 6). Therefore, a limited share of DR and medium-term EES improve system adequacy and reduce consumer cost in an energy-only market. These results also indicate that CM with EES (experiment 6) also performs better in terms of consumer costs then a CM without EES (experiment 3), but not better than a system with CM, DR and EES (experiment 4 and 5). Therefore, as per our results, the case for a CM is weakened if DR and EES are included in an energy-only market.

The performance of EES (as indicated in Fig. 16) in different experiments is gauged by the average number of discharging cycles. Discharging cycles are calculated by dividing the total annual output of the EES by the total energy storage capacity. The performance of EES is almost similar in experiments 2, 3 and 4. The performance of EES is slightly better in experiment 6 as it takes advantage of price arbitrage between peak and off-peak hours in the absence of DR. With the increasing share of RES-E in the system, the performance of EES improves. The marginal drop in discharging cycles seen in all experiments occurs as generation capacity that was under construction comes online.

Fig. 17 shows the volume of EES capacity for all the runs for experiment 2. The volume of EES capacity in all the other experiments does not change. The capital and operating costs are generally not recovered, so significant investment in EES is not observed. In case of a technological breakthrough in EES technology that would reduce its costs significantly, more investment might occur [70]. Details about the share of EES in the supply mix can be found in Table D.5 in Appendix D.

These results indicate that allowing EES to participate in a CM could reduce the cost of CM. However, the business case for EES is better in an energy-only market as it can take advantage of the scarcity prices, in contrast to a system with a CM in which electricity prices are dampened due to excess supply. The capacity contribution of EES to the CM is adequate as the EES can only commit capacity that can be discharged during a peak load hour.

Remuneration of EES from the CM is not high enough to significantly contribute to its revenues. A lower reserve margin of 8% [113] was chosen for this study as compared to a reserve margin of more than 16% [134] in order to account for the fact that we do not model generator outages. However, the CM clearing prices are still not high enough to adequately remunerate EES. It appears that the capacity obligation can be further optimized while maintaining security of supply and strengthening the business case for EES.

Fig. 18 shows the volume of elastic load in MW in experiment 2, 4 and 5 in which DR is included. The figure also shows the year-on-year growth trend of the elastic load.

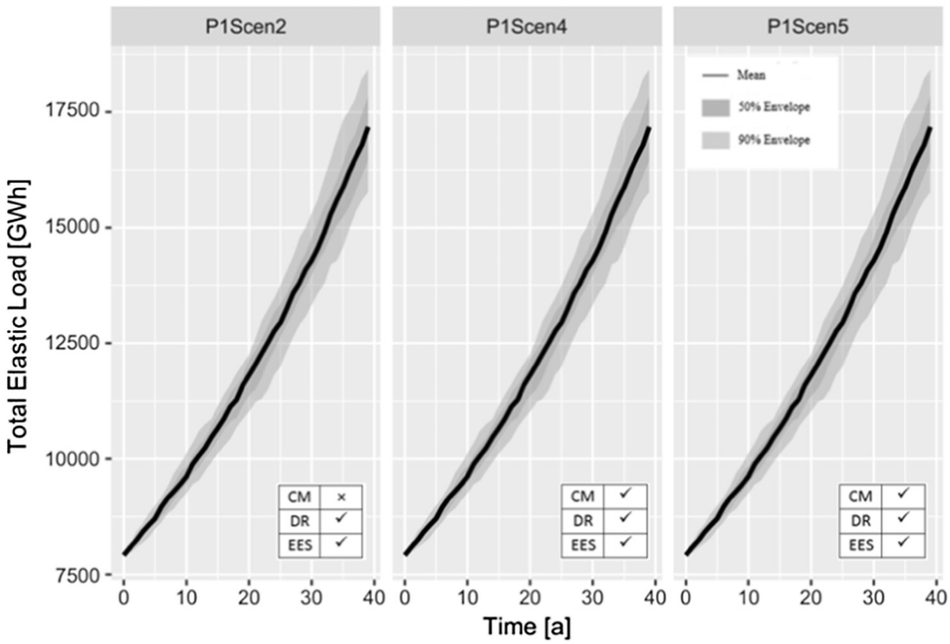

Fig. 18. Volume of elastic load (GWh/year) in experiments 2, 4 and 5 (in that order).

5.4. Policy recommendations

On the basis of these results, we make three policy recommendations. First, incentives for investment in EES and DR will help improve system adequacy in an energy-only market with investment cycles and should therefore be included in the design of a CM. Thus, a fair compensation mechanism needs to be designed for valuing the contribution of EES to system adequacy in a CM. We propose a simple rule for allowing EES to participate in a CM; however, the variety of EES technologies and greater weather uncertainty in practice may require a more elaborate approach. Second, the positive effects of EES may support the case for subsidizing the development of this technology. Third, we do not recommend that DR should receive capacity credits because of difficulty with establishing the reference consumption pattern for small users and the subsequent risk of gaming. Only industrial DR, with verifiable contributions, that is available at a price higher than the price cap, should be allowed to sell capacity credits. DR that is active at lower prices will naturally reduce peak demand and therefore the capacity obligation and can therefore be considered to participate implicitly.

6. Conclusions

Whereas capacity markets (CMs) ensure security of supply by providing investment incentives, consumer-side flexibility options like demand response (DR) and electrical energy storage (EES) contribute to system adequacy by reducing residual peak loads. Therefore we studied the impact of flexibility options vis-à-vis a CM on security of supply. We analyse an isolated uncongested electricity market (based on the Netherlands) with an endogenous carbon emissions market (based on a scaled-down version of the European Emission Trading System (EU-ETS)). We perform six experiments with different combinations of policy instruments, stochastic electricity demand growth and fuel prices.

We perform our analysis with a hybrid electricity market model with autonomous competitive agents (power companies) who make investment decisions (in generation & EES capacity) with imperfect foresight. We consider the model a hybrid because short-term market dynamics in the model (dispatch and price formation) including intertemporal dependencies caused by DR and EES are simulated using an optimization method. This model is a substantially modified version of the agent-based model of Bhagwat [107] and Richstein [111]. The main change is the clearing of electricity market on hourly basis, enabling us to assess the impact of intermittent renewables and the intertemporal effects of DR and EES. While the short-term objective is to minimize the cost of generation, carbon credits, DR and EES, the long-term behaviour helps us study individual agent investments and emergent system evolution. Endogenous investment in EES enables us to optimize its capacity. We also introduce a mechanism for participation of EES in the CM is proposed by setting the volume of capacity credits the CM may sell to EES equal to its energy storage capacity divided by the number of hours it needs to be available.

Our results indicate that the case for a centralized CM is lessened by even a limited share of DR and medium-term EES in the electricity market. In our model, the CM ensures security of supply and also decreases consumer costs, but not as much as DR and EES. If a CM is implemented in an electricity system with DR and EES, the capacity obligation can be reduced significantly, reducing the consumer cost. However, refinement of the model representation with other types of DR, EES and CMs will be required to evaluate whether, when and how much share of these flexibility sources will be enough to remove the need for a capacity mechanism altogether. A particular concern is the occurrence of severely adverse but irregular weather events, such as extended periods with cold weather and/or low wind availability. However, even if DR and EES alone are not enough to maintain a sufficient level of system adequacy and a CM is added, its design needs to take the presence of these flexibility options in consideration and stimulate their development.

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[3] eacea.ec.europa.eu/.

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Appendix A

See Fig. A1.

		NEM	TGT	SD	SG	ABM
Problem definition	Communicate with experts			x	x	
	Parameterize problems	x	x	x	x	x
	Identify and define population		x		x	x
	Identify resources, system characteristics and boundaries				x	
Evaluation criteria	Specify measures				x	
	Measure clarification and link with problem definition	x	x	x	x	x
	identify and consider extreme values	x	x	x		x
Identification of policy alternatives	Identify policy attributes			x	x	x
	Link policies to evaluation measures	x		x	x	x
	Include technical, political and economic aspects	x		x	x	
	present policy alternatives			x	x	
Decision support for selecting policy alternatives	Compare alternatives	x		x		x
	Participatory decision making				x	x
	Answer what-if scenarios	x		x	x	x
	Explore possible reactions towards policies					x
	Test extreme values	x	x	x		x
Monitoring	Compare before and after situations	x	x	x	x	x
	Track reactions					x

Fig. A1. Comparison of different policy analysis approaches for distinctive problems (NEM: Neo-classical Equilibrium Modelling, TGT: Traditional Game Theory, SD: System Dynamics, SG: Serious Gaming, ABM: Agent-based Modelling) from [167].

Appendix B

See Figs. B1 and B2.

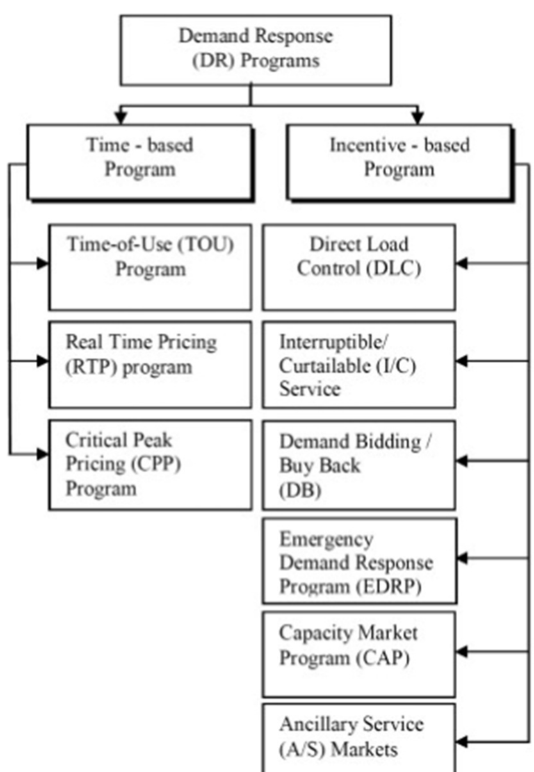

Fig. B1. Categories of demand response programs from [56].

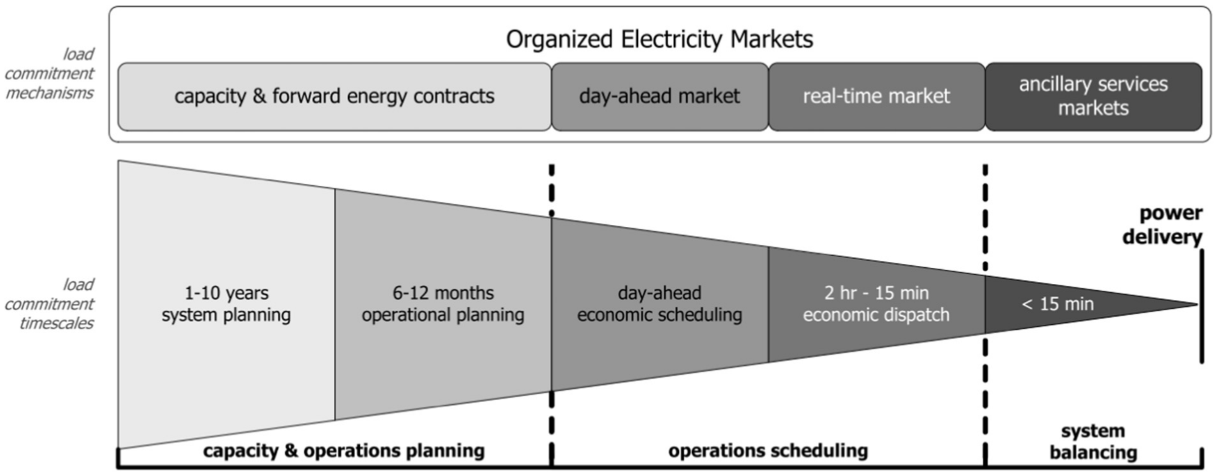

Fig. B2. Demand response planning and scheduling: timescales and decision mechanisms from [168].

Appendix C

See Figs. C1–C3.

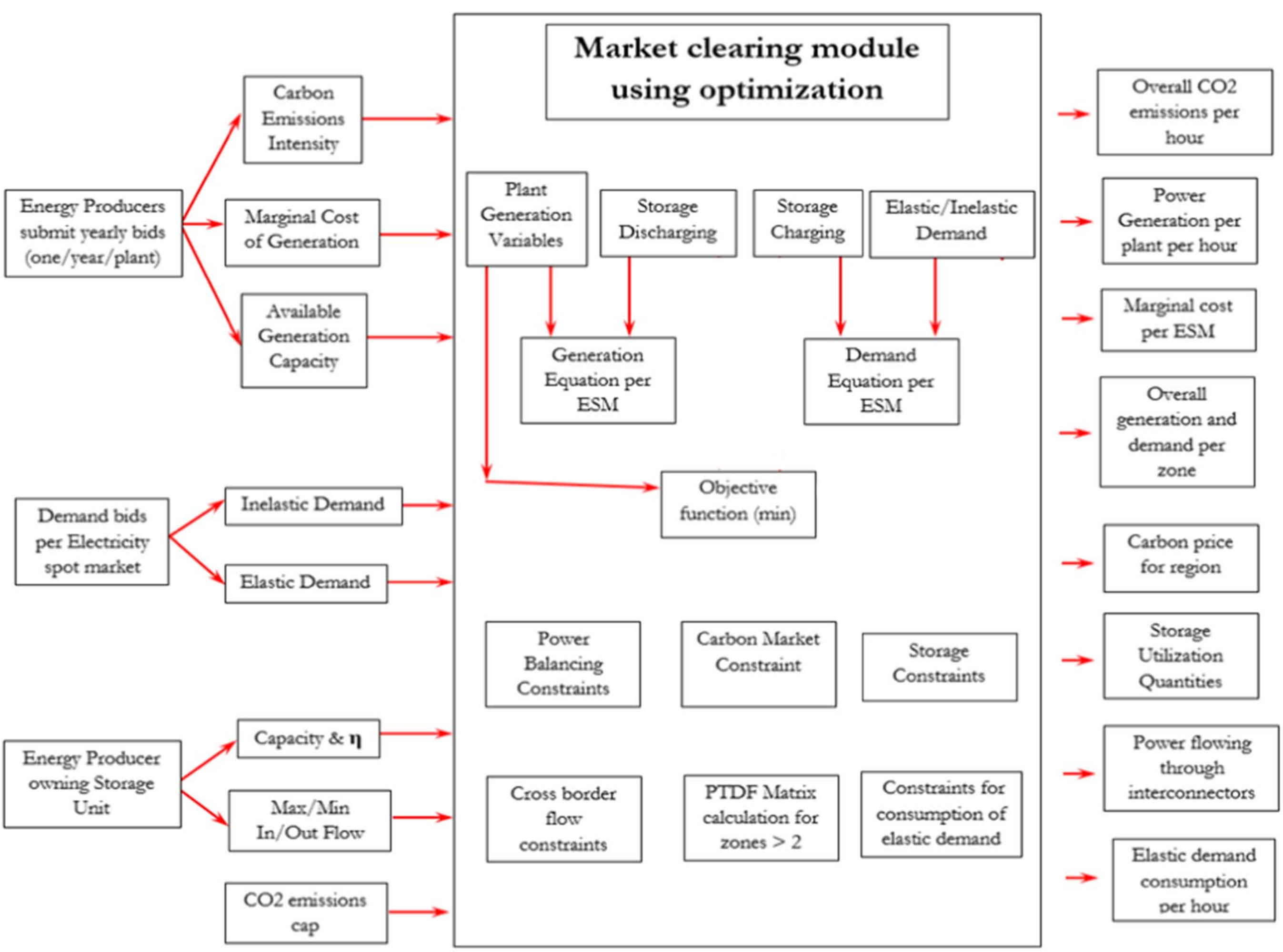

Fig. C1. Market clearing optimization role for a year in the model.

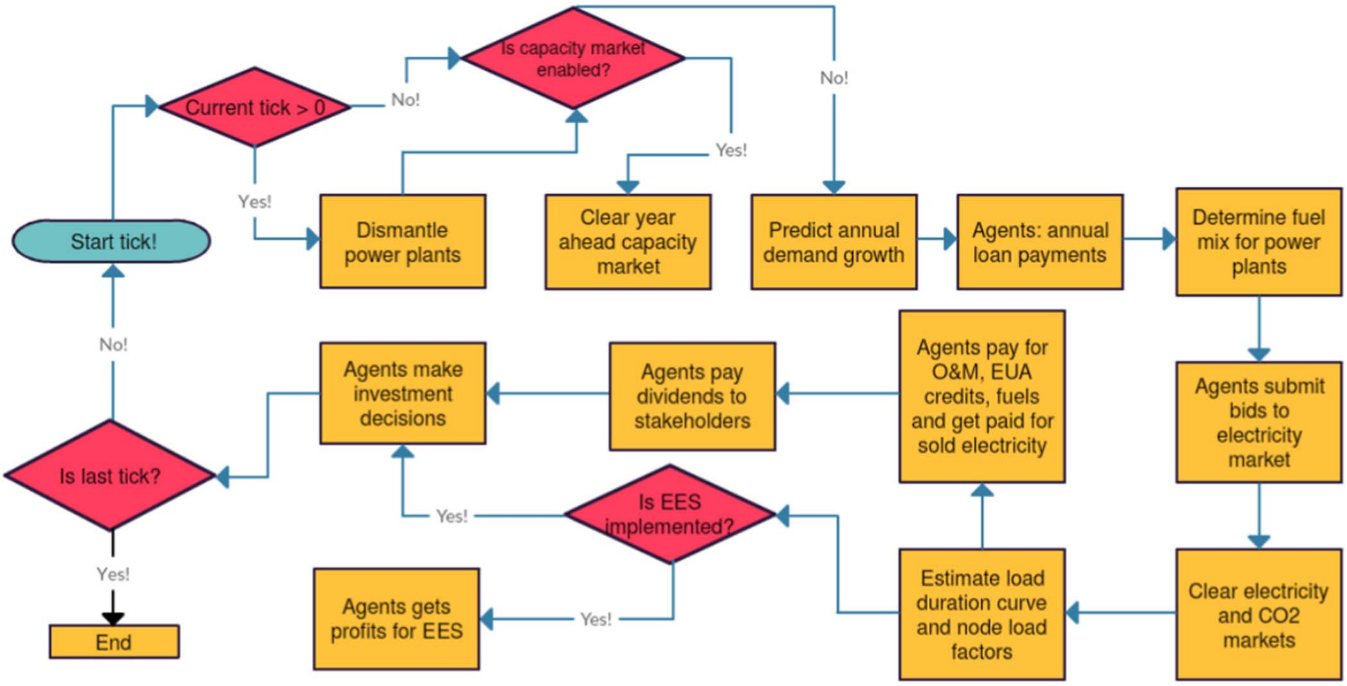

Fig. C2. Stylized flow chart for a year in the model.

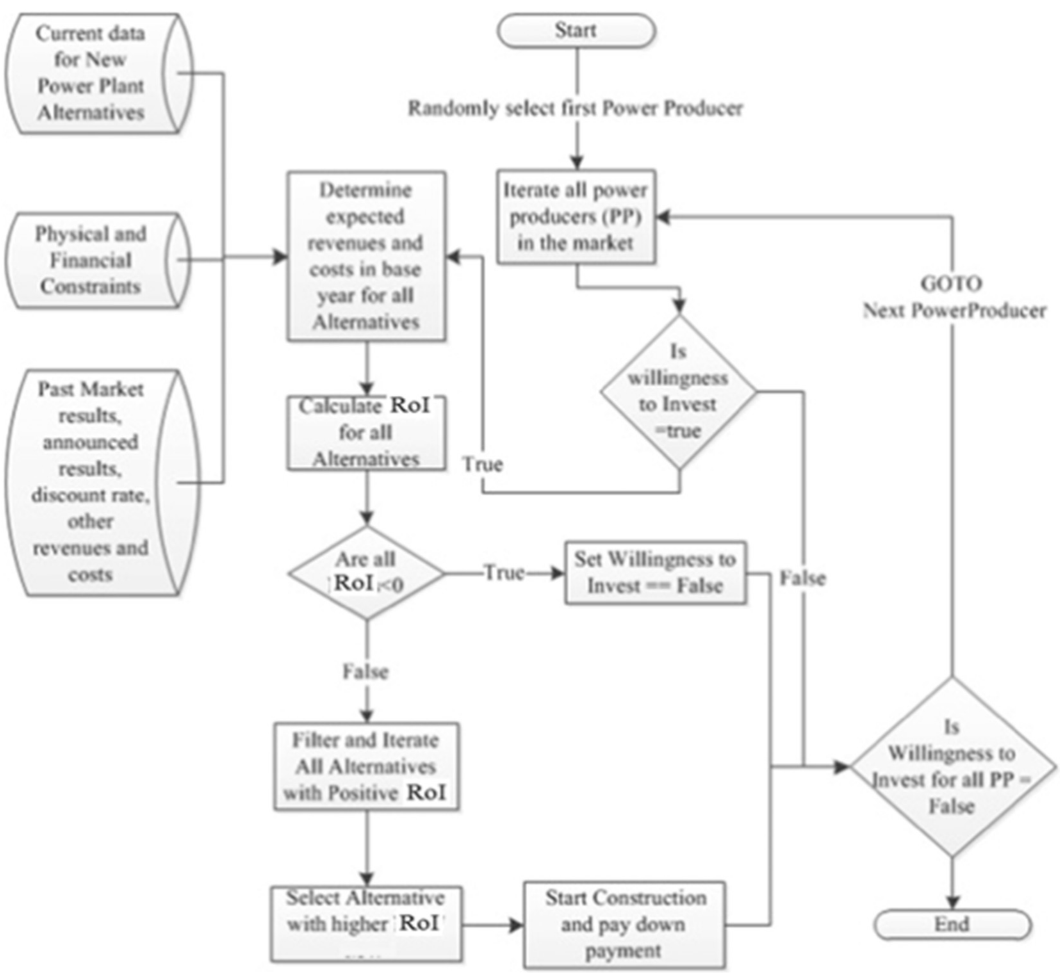

Fig. C3. Stylized flow chart for the investment role. Adapted from Bhagwat et al. [126].

Appendix D

See Tables D1–D5.

Table D1
Power generation technology assumptions [5].

Generation technology	Capacity [MW]	Construction time [yrs]	Permit time [yrs]	Technical lifetime [yrs]	Depreciation time [yrs]	CO_2 capture eff. [%]	Min. running hours [h]	Base availability	Peak availability	Fuel(s)
Nuclear	1000	7	2	40	25	n.a.	0	1	1	Uranium
Coal Pulverised SC	758	4	1	50	20	0	0	1	1	Coal, Biomass (10%)
CoalPSC with CCS	600	4	1	50	20	87.5	0	1	1	Coal, Biomass (10%)
Biomass combustion	900	3	1	40	15	0	0	1	1	Biomass
CCGT	776	2	1	40	15	0	0	1	1	Gas
CCGT with CCS	600	3	1	40	15	85	0	1	1	Gas
Hydro	1000	5	2	100	30	n.a.	0	0	0.6	n.a.
Wind	900	1	1	25	15	n.a.	0	0.4	0.24	n.a.
Wind offshore	900	2	1	25	15	n.a.	0	0.6	0.32	n.a.
Photovoltaic	900	2	1	25	15	n.a.	0	0.2	0.08	n.a.

Table D2
Fuel price and demand growth rate assumptions.

Type	Unit	Demand growth rate	Coal	Biomass	Gas	Uranium
Start	€/GJ	1.02	2.88	4.8	7.02	1.24
Average	€/GJ	1.02	2.89	4.75	7.1	1.245
Upper	€/GJ	1.03	3.1	5.5	7.2	1.29
Lower	€/GJ	1	2.68	4	7	1.2

Table D3
Cost of pumped hydro storage systems. Data based on Zakeri and Syri [70], Van Staveren [169] & IRENA [144].

Item	Cost
PCS + BOP[a] (€/kW)	425
Storage section(€/kWh)	41
Fixed O&M (€/kW-yr)	3.9

[a] Balance of plant.

Table D4
Parameters for EES system. Data based on Zakeri and Syri [70] and Van Staveren [169].

Parameter	Value
Charging time [hours]	24
Discharging time [hours]	24
Efficiency (%)	90

Table D5
Initial and final supply mix including EES with increasing share of RES.

Generation technology	Scenario 1 initial Mix [%]	Scenario 1 final Mix [%]	Scenario 1 final Mix [GW]	Scenario 5 initial Mix [%]	Scenario 5 final Mix [%]	Scenario 5 final Mix [GW]
Nuclear	1.46	0	0	1.46	0	0
Coal Pulverised SC	21.6	6.02	8.21	21.6	6.99	9.63
CoalPSC with CCS	0	0	0	0	0	–
Biomass combustion	3.77	7.38	10.06	3.77	7.3	10.06
CCGT	61.5	9.14	12.46	61.5	9.68	13.34
CCGT with CCS	0	0	0	0	0	0
Hydro	0.11	0.028	0.038	0.11	0.027	0.038
Wind	7.86	22.01	30.01	7.86	21.78	30.01
Wind offshore	0.67	41.73	56.9	0.67	41.31	56.9
Photovoltaic	2.97	13.67	18.64	2.97	13.53	18.64
EES	–	–	–	5.09	1.22	1.68

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