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Capacity remuneration mechanisms for decarbonized power systems

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HIGHLIGHTS

- In a system with high renewable energy and high flexibility, the use of a strategic reserve may increase the volatility of electricity prices. It will also be difficult to parametrize.
- With a capacity market, the parametrization of the demand curve and the derating factors also become more challenging in a system with more renewable energy and flexibility.
- A capacity subscription reveals the consumers' need for capacity during scarcity periods. However, the short contract duration may lead to investment cycles or to under investments if consumers do not consider the risk of extreme weather events.

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ABSTRACT

Motivated by generation system adequacy concerns, many European countries have introduced capacity remuneration mechanisms (CRMs) to ensure sufficient investments in power generation. However, it is uncertain whether the existing CRMs will promote sufficient adequacy and flexibility in a decarbonized power system, where supply and demand will become more weather-dependent. We assess the effectiveness of a centralized capacity market, a strategic reserve, and a decentralized capacity market via capacity subscriptions in a climate-neutral, weather-driven power system. We develop a co-simulation of two agent-based models simulating myopia in both operational and investment decisions. We simulate weather uncertainty by running the model with 40 different weather years. Our results from a case study based on the Netherlands indicate that a strategic reserve may increase electricity price volatility in the long-term. A centralized capacity market is more cost-effective than a strategic reserve, but administratively setting its parameters is prone to over- or underprocurement. Capacity subscription allows consumers to select their desired level of reliability. Results indicate that these decentralized capacity markets may yield a clearer signal for the needed dispatchable capacity and promote demand-side response, but it may be challenging to provide long-term certainty for investors.

1. Introduction

Uncertainty regarding commodity prices, CO_2 prices, demand growth, technological breakthroughs, and regulatory interventions, coupled with increasing weather dependence in a future system with nearly 100 % electricity produced from variable renewable energy (VRE), and missing markets are reasons why investors in liberalized electricity markets may not have enough incentives to invest in sufficient capacity to ensure system adequacy [1]. We investigate the effectiveness of various capacity remuneration mechanisms (CRMs) in ensuring that there are enough resources to meet demand (up to a predefined reliability standard). Capacity remuneration mechanisms have been on the rise in recent years in Europe; from 2020 to 2022, the yearly cost of these mechanisms has doubled to 5.2 bn Eur [2]. Recently, Spain and Germany announced that a CRM will be introduced [3,4]. The EU used to consider CRMs as temporal measures, but now acknowledges that they may be needed permanently [5].

In this study, we compare an energy-only market (EOM) with a strategic reserve (SR), a capacity market (CM), and a capacity subscription (CS) in a defossilized future power system in the Netherlands. We consider an EOM to be the reference case because it is the current market design in the Netherlands. We compare this to a CM because it is widely implemented across the world, and an SR because it is

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Nomenclature

Abbreviations

ABM Agent-based model
AO Affordability options
$ACER$ Agency for the cooperation of energy regulators
$AMIRIS$ Agent-based market model for the investigation of renewable and integrated energy systems
$BESS$ Battery energy storage system
CM Capacity market
$CONE$ Cost of new entry
CRM Capacity remuneration mechanism
CFD Contract for difference
CS Capacity subscription
DSR Demand side response
$EMLabpy$ Energy modelling laboratory Python
EOM Energy only market
EU European Union
EV Electric vehicle
HP Heat pump
IRM Installed reserve margin
LS Load shedding
$ORDC$ Operating reserve demand curve
PaC Pay as cleared
RO Reliability option
RS Reliability standard
SDC Sloped demand curve
$SFPFC$ Standardized fixed price forward contracts
SR Strategic reserve
$VOLL$ Value of lost load
VRE Variable renewable energy
WTP Willingness to pay

Indices

g Generator
t Time steps during market clearing horizon
y Year
h Hour
CG Consumer group

Sets

G^{SR} Set of all generators in SR
T^{SR} Set of all time period when SR is active

Parameters

$CAPEX$ Capital expenditures
D/E Debt-to-equity
ρ Debt interest rate
D Demand
DP Downpayment
FC Fixed cost
i Equity interest rate
IRR Internal rate of return
L Loans
$OPEX$ Operational expenditures
VC Variable cost
T_C Construction time
T_{EL} Expected lifetime
$WACC$ Weighted average cost of capital

Variables

DF Derating factor
ENS Energy non supplied
$H_2\,T$ Hydrogen production target
K Capacity
π Annual profit
Lo Loans
$LOLE$ Loss of load expectation
NPV Net present value
p Wholesale market price
q Energy produced

recommended by the EU regulation.[1] The last option we review is CS, a not-yet implemented nor well-studied decentralized type of CRM that provides better incentives for demand-side response, which will be greatly needed in a power system dominated by weather-dependent electricity production.[2]

Previous studies have simulated CRMs with optimization models[7], system dynamics [8], and equilibrium models [9,10]. Most of these studies model a benevolent central planner, assume market equilibrium and perfect foresight, and don't consider the lumpiness of investments. Agent-based models (ABMs) offer an option to represent myopic investments where investors build new power plants as long as they are expected to be profitable, with no guarantee of long-run equilibrium and considering the lumpiness and time lag in the commissioning of investments as explained in Section 3.1.2. Due to this lumpiness, more capacity may be installed than strictly needed to meet the demand for capacity, which can lead to volatile CM prices [11].

Capacity mechanisms have been modeled with various ABMs. PowerACE was employed to model the German transition and the cross-border interaction [12]. EMIS-AS was applied to model the transition [13]. EMLab [14] was used to study a strategic reserve and a capacity market. Nevertheless, those models simulate dispatch decisions with (linear) optimization problems while we apply another ABM for the short-term market, AMIRIS [15]. In AMIRIS, the dispatch is not based on a central objective function with perfect foresight, but rather on the interplay of agents and robust storage dispatch strategies that cause an efficiency gap in comparison to an optimization approach [16,17]. Through a co-simulation, we use the strengths of both models; EMLabpy (which is based on EMLab) simulates investment decisions, while AMIRIS simulates dispatch decisions with flexible generators, representing myopic behavior in the long-term investment decisions as well as in the short-term dispatch decisions. This is relevant considering that models with perfect foresight can exaggerate the value of storage [18]. Furthermore, previous studies have shown that power system optimization models with perfect foresight tend to underestimate total system costs and overestimate the decarbonization pace in comparison to myopic investment models, which better reflect real-world conditions. There is also some evidence that myopic investment can result in stranded assets, as investments are optimized in the short-term rather than in the long-term [19,20], but on the other hand, myopic decisions may lead to underinvestment.

We find that a capacity market incentivizes more capacity with more stability, but there is a risk of incorrectly parametrizing the demand and the contribution of supply. With a strategic reserve, the use of the reserve might become volatile, which causes high and volatile electricity prices. Finally, in capacity subscription, the DSR of consumers can regulate the demand for capacity, but there is a risk of investment cycles due

[1] In case a Member State has resource adequacy concerns, the EU recommends implementing a strategic reserve [6], and if an SR is insufficient, an alternative CRM may be considered.

[2] We use the term decentralized market to refer to the case where the demand for capacity is decentralized (following the logic of the *decentral capacity obligations* used by ACER [2]). Note, however, that buyers and sellers in CS meet in an exchange, similar to a central capacity market.

to consumers drastically changing their willingness to pay and a lack of long-term contracts.

The rest of the paper is organized as follows, Section 2 offers a synthesis of the current literature around implemented CRMs and provides an overview of the new CRM proposals for power systems with high share of VREs and high flexibility. Section 3 explains the applied co-simulation and how the strategic reserve, capacity market, and capacity subscription are modeled. Section 4 describes the data and the scenarios. Section 5 presents the results from the analysis, and their implications are discussed in Section 6. Finally, Section 8 concludes by summarising the paper's main findings.

2. Literature review

According to the theory of optimal spot pricing, an energy-only-market (EOM) can incentivize enough investments if, during scarcity, prices rise above the marginal costs of the peak technology to the willingness to pay of consumers [21,22]. However, this applies to a market under "ideal" conditions, such as with risk-neutral actors, perfect foresight, perfect competition, complete markets, etc. [23]. However, in reality, these ideal conditions are not met. In many markets, price caps are set to a value lower than the value of lost load (VOLL), leading to the so-called 'missing money problem', as they reduce the expected average revenues of generation companies, and thereby reduce the incentive to invest. Moreover, without real-time prices, consumers' willingness to pay (WTP) cannot set the price during scarcity periods. Furthermore, the high share of VREs depresses prices in times of abundant wind and solar energy, and the availability of flexibility is uncertain. Risk aversion and high uncertainty, exacerbated by the energy transition, further discourage investments in the absence of complete markets for risk trading [24].

The EU argues that scarcity prices should provide incentives to retailers to hedge via forward markets. However, government interventions during periods of high prices, consumer contracts with durations of 3 years or less, and the ability of customers to switch between retailers prevent retailers from signing long-term contracts [23]. Assuming individual consumers cannot (e.g., due to the absence of smart metering infrastructure) or may not be disconnected selectively (e.g., due to regulation), retailers that have hedged enough energy are likely to be curtailed at the same level as those that did not hedge their position. This makes resource adequacy a public good, and creates a "missing market" for forward contracts, as Wolak explains [25]. Additional factors contributing to the illiquidity of long-term markets, as identified by Batlle et al. [26], include the absence of demand response and policy interventions during periods of stress, among others. Ren et al. [27], on the other hand, argue that with the advent of smart meters, resource adequacy can be treated as a private good, as these devices allow disconnecting or limiting the offtake of consumers selectively. While such an approach is not devoid of disadvantages, it would allow for more advanced capacity remuneration mechanisms, such as capacity subscription.

CRMs have been introduced across the world to alleviate the missing money and missing market issues. In what follows, we subsequently discuss different capacity remuneration mechanisms (CRMs), differentiating between those that have been implemented (Section 2.1) and those that have been proposed for power systems with high shares of weather-dependent generation (Section 2.2).

2.1. Current capacity remuneration mechanisms in Europe

In general, CRMs are designed in such a way that the reliability standard (RS) is met. The RS is the socioeconomically optimal level of supply security. It is the level at which the cost of additional capacity (defined as the cost of new entry, CONE) and the maximum that consumers are willing to pay to avoid a supply interruption (defined as the value of lost load, VOLL) are balanced [28].

A capacity market is a market-wide mechanism in which power plants are contracted and receive annual payments for being available during stress events. In a centralized CM, the demand for capacity is set administratively through a sloped demand curve (SDC).[3] In contrast, in a decentralized CM, retailers or consumers receive a capacity obligation to ensure availability with their generators, capacity certificates, or bilateral contracting. Large consumers are incentivized to flexibly schedule their demand to minimize capacity payments [30].

Implementing a capacity market requires estimating each technology's contribution to the reliability of the power system. Derating factors (DF) are "the statistical degree to which the installed capacity is expected to contribute to resource adequacy when energy not served (ENS) occurs" [28]. If the central authority sets the DFs too high or too low, some technologies can be favored over others. Excluding some technologies may lead to welfare loss, as their potential would be ignored [31]. Remunerating batteries and energy or duration-limited demand response for their availability is not straightforward. They may not be available during scarcity events due to their energy-limited nature and imperfect foresight. This should be considered in adequacy assessment guidelines [32].

Although the European electricity regulation stipulates that CRMs should be technology-neutral [6], in practice, each country rewards different types of generators. VREs are allowed to participate in many capacity markets (for an overview of these, refer to [30,33,34]). In the presence of effective penalties for not delivering, the participation of VREs in a CRM could expose them to significant risk, leading to generators charging an extra premium or limiting the capacity that they offer to the market. In the opposite case, in which VREs are not awarded in a CM, their contribution to peak demand should be deducted from the administratively set demand for capacity [35]. Lynch et al. [36] showed that with high VREs, CM prices can increase, but demand-side response (DSR) can help keep capacity market prices low as it also contributes to more scarcity prices in the energy-only market.

To provide capacity providers an incentive to be available during periods of scarcity, some capacity markets feature penalties for non-delivery during scarcity periods, such as in the reliability options used in the Belgian CRM [37]. In this mechanism, generation companies sell call options to the TSO or to retail companies. The seller agrees to supply energy when the market price surpasses a strike price and to return the difference between the market price and the strike price to the buyer. If the seller cannot deliver during scarcity moments, i.e., when the market price is higher than the strike price, then the seller still needs to return the difference between the market price and the strike price. This can be considered an implicit penalty. ROs can be organized centrally or bilaterally, and there are multiple design options with respect to the reference market, the indexation, the penalties for underperformance, the capacity commitment, etc. [38]. Reliability options (ROs) can be used in centralized capacity markets to provide revenue clawback during periods of high wholesale market prices [39,40].

As an alternative to a capacity market, a strategic reserve is a mechanism that intends to maintain some plants as a backup, taking them out of the market and dispatching them at a high price only when the market is not cleared in the day ahead or intraday markets. The mechanism intends to extend the lifetime of these power plants in case adequacy is at risk.

2.2. Proposals for CRMs in power systems with a high degree of renewables and demand side flexibility

In current centralized CMs, a central authority is responsible for estimating the capacity needed to ensure reliability. This authority doesn't face penalties or rewards for over- or under-investing other than the political pressure to avoid shortages. Consumers are the ones who bear the consequences, either of lost load or of over-contracting, with no possibility of managing their risks and preferences [41]. In contrast,

[3] It is typically sloped to prevent market power and to create some elasticity [9,29].

in decentralized CRMs, the responsibility for setting the demand for capacity is shifted from retailers and TSOs to consumers, incentivizing them to manage their energy consumption during periods of scarcity and providing an intrinsic incentive for flexibility. Instead of building more capacity, consumers' flexibility can help reduce the need for peaker plants, thereby reducing the system's costs. In addition, the quality of supply can become a private good. In recent years, several proposals have emerged to achieve this.

The missing markets and missing money can be remediated with capacity payments, forward energy trading, or enhanced scarcity pricing. In recent years, there have been more proposals to achieve resource adequacy through long-term energy products (paying for energy instead of capacity). For example, Wolak [25] proposed Standardized fixed price forward contracts (SFPFC) where retailers are obliged to hold shaped forward contracts for energy. The contract is settled ex-post to match the actual load over the delivery period, but the energy price is determined in advance. Similarly, Batlle et al. [26] proposed that suppliers should ensure a level of hedging. Furthermore, Bilimoria et al. [41] proposed a mechanism in which consumers with a high VOLL pay for insurance to avoid being curtailed, and the insurer-of-last-resource uses the insurance premium to pay for the costs of plants in a strategic reserve.

Others have proposed improving short-term markets, typically with the aim to strengthen the frequency and predictability of scarcity prices. A notable example is the operating reserve demand curve (ORDC). This mechanism intends to reflect the value of reserves based on how scarce they are. It can be seen as a no-regret measure because these price adders make no difference in the case of abundant flexibility [42]. Note that CRMs and improvements to short-term markets and long-term energy trading are not mutually exclusive. However, in this research, we focus on CRMs that improve resource adequacy by remunerating capacity.

The European Electricity Regulation stipulates that CRMs should promote non-fossil flexibility resources such as DSR and storage in CRMs [43]. Due to the electrification of much of industry, transport, and HVAC, DSR has an increasing potential to reduce the peak loads and, thus, the total system costs. In CMs, DSR has been included by allowing it to participate on the supply side as providers of interruptible capacity (typically with a limited duration and with specific derating factors). However, Apostolopoulou and Poudineh outline some issues with the participation of demand-side responses in the supply-side of capacity markets. One of them is the long lead times between the capacity contract and the delivery obligation. Further, in some CMs, there is no limit to the time during which DSR should be available. More relevant is that DSR does not have a schedule obligation and can offer its capacity at a high declared price [34]. Lambin [44] argues that DSR with very high activation prices (at VOLL or higher), therefore activated very seldomly, should receive lower capacity payments.[4] Finally, there is a risk of manipulation of the baseline consumption pattern, which requires verification methods. These issues could be avoided if DSR could participate on the demand side of the capacity market. In what follows, we'll introduce some proposals for doing so.

2.2.1. Mechanisms to unlock DSR in capacity markets

Capacity Subscription (CS) allows consumers to subscribe to their indispensable capacity during scarcity, explicitly participating on the demand side of the capacity market. In this way, the demand curve for the capacity market is no longer set with a single weighted average VOLL, as it is done with current capacity markets [28], but through a decentralized demand for capacity. Similar to a yearly CM, generators recover part of their costs from the CS subscription. Consumers buy the capacity credits at the volume that they need, and if the CS price is expensive, they would start looking for alternatives (such as batteries, EV charging, home energy management systems, etc.) to become more flexible and keep their subscribed capacity low [46,47]. The implementation of CS requires the installation of smart meters. In countries like Spain, where consumers are already asked to declare their valley and peak consumption contracted capacity, asking them for their desired capacity in times of scarcity would not be a big effort [48].

In times of scarcity, the load-limiting devices restrict consumption to the subscribed capacity levels. It may be a challenge for household consumers to select the level of capacity to which they subscribe. Options include basing it on their previous year's needs and requiring a minimum capacity subscription. Retailers might need to inform consumers about the most likely times when scarcity could emerge. In times of scarcity, consumers should be warned some time in advance. The subscriptions are traded in annual auctions in advance of the season, and the subscription is valid for one year. Another detail to consider is a secondary market where consumers could adjust their contracted volume, i.e., when their living situation changes.

The original proposal for CS does not directly protect consumers from high prices. The assumption was that by avoiding physical shortages, the electricity price would stay close to the marginal cost of generation of the most expensive unit during near-scarcity periods. However, in a future market with a high volume of flexible demand – which may have a high willingness to pay – certain consumers, like households, may want more certainty. As we do in this paper, it is possible to combine CS with a clawback, such as an individualized reliability option, i.e., a pre-agreed or regulated maximum price, in exchange for the capacity payment that is made by the consumer, as proposed by de Vries [49] and Hu et al. [50]. In this case, power plants that have sold capacity credits are required to return profits from selling electricity above a pre-agreed strike price to consumers for the volume of subscriptions that consumers purchased [51].

A similar mechanism is priority pricing, in which consumers subscribe to multiple capacity strips (with different electricity prices) according to their flexibility. A higher electricity price is paid for more essential segments of demand, which have a lower chance of being curtailed. Aggregators offer a menu of reliability price–quantity pairs and aggregate consumers' subscriptions to participate in the demand side of a CM [34,52]. A similar implementation is multilevel demand subscription (MLS), where consumers adapt their subscription based on the duration of the shortage. Mou et al. compared priority pricing against a multilevel demand subscription (MLS) and found that with an MLS, the subscribed energy demand is better approximated to the real consumption of households, which makes them subscribe to less energy and more capacity, incurring lower total costs [53].

3. Methodology

We simulate a fully decarbonized power system and study the performance of an EOM, an SR, a CM and CS subject to inter-annual weather variability. We have created a co-simulation between two ABMs, AMIRIS and EMLabpy, thereby combining the strengths of widely tested models. AMIRIS simulates bidding behavior in power markets. Power plants owners maximize their profits considering limited foresight. They bid in the wholesale market according to generation and electricity price forecasts [15]. EMLabpy simulates investment decisions based on AMIRIS market results. We simulate a single myopic agent that invests in power plants as long as their expected NPV is positive. To simulate weather uncertainty due to weather-driven generation and temperature-dependent loads, we test 40 years with different weather profiles (based on the historical weather profiles from 1980 to 2019 (see Section 4.1). However, the investment decisions are based on a *representative* weather year. This co-simulation allows us to represent the effects of myopic investment decisions based on market results from myopic short-term market participation decisions.[5] The code and all data required for our case

[4] In the Belgian CM, DSR is derated by the number of hours that it can be activated but does not consider the activation price[45].

[5] Furthermore, the co-simulation allowed us to store the data in two databases and to minimize the information read by each module, as needed. For example,

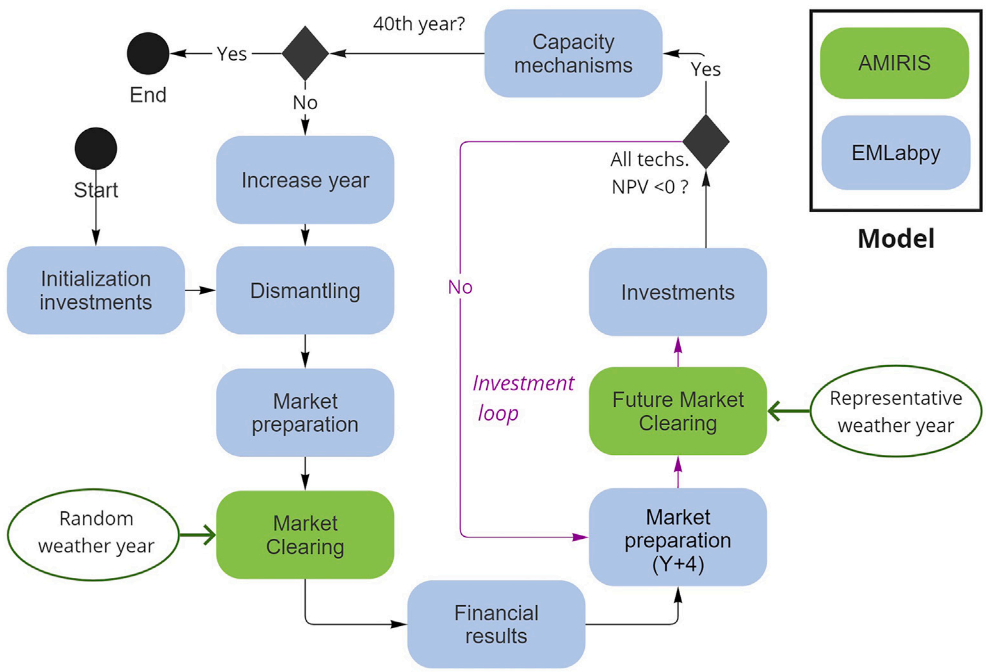


Fig. 1. Overview of the co-simulation methodology.

study (see Section 4) can be found at https://github.com/TradeRES/toolbox-amiris-emlab.

The subsequent section provides an overview of the co-simulation workflow, followed by an explanation of the logic behind the investment and decommissioning decisions.

3.1. Workflow

Fig. 1 shows the co-simulation workflow. We conduct an investment loop prior to the start of the year-by-year simulations to account for a possible need for investment at the start of the simulation. The year-by-year workflow commences with dismantling power plants that have reached their lifetimes and are unprofitable (see Section 3.1.3). Next, the portfolio of power plants in the model is transferred from EMLabpy to AMIRIS, which simulates hourly wholesale market bids, prices, and revenues, based on distinct weather and load profiles. The financial performance of all generators is registered. Then, investment decisions are made iteratively based on the forecast of future market outcomes by AMIRIS (see Section 3.1.2). As a final step, the capacity payments are computed, considering the CRM design at hand.

3.1.1. Dispatch in AMIRIS

In AMIRIS, dispatch decisions are modeled with an hourly resolution for a weekly rolling time horizon. Storage is scheduled with the robust strategy, where bids are based on an initial forecast of electricity prices with a margin. This forecast is based on the bids of inflexible agents and VREs availability. See Section 4.1.3 for a further description of the flexible load representation and [15] for more details about AMIRIS.

3.1.2. Investment decisions

In each year y, EMLabpy's investment decisions are made by iteratively evaluating the anticipated profitability of candidate technologies in market results four years ahead (Y + 4). The candidate technology with the highest anticipated NPV is scheduled to be installed and commissioned in year Y + 4. The future availability of these plants is factored into the expected revenues for subsequent investments. As a result, each additional power plant has lower expected revenues. When the profitability expectation for all technologies falls below zero, the investment cycle ends. This approach leads to a 'pipeline' of plants that are under construction. To maintain computational feasibility, new plants are grouped by technology and commissioning year. Due to the iterative process, the technologies selected for investment in the first iterations, with the highest expected NPVs, may perform worse than expected due to consecutive investments in later iterations in the same simulation year.

Some technologies have a shorter lead time than four years. Nevertheless, they are installed in the year of the market's estimation (Y + 4) to prevent investment cycles, as more capacity would be installed than anticipated.[6] The weather and demand profiles for the future market estimation are based on a representative historical year with a median renewable energy production level (2004 in our data set, see Section 4).

3.1.3. Decommissioning

To simulate the fact that older power plants are more inefficient and therefore enter the merit order curve at a lower rate than newer plants, the variable costs of installed power plants increase by 0.005 % each year.[7] To represent the irreversibility of investments, we consider that generators are dismantled only after their technical lifetime has been reached, meaning that there are no early retirements. If the average net profits of the past four years have been positive, then the lifetime of a plant is extended (up to a predefined maximum per technology), and its fixed costs are raised. All revenues and costs are considered to determine profitability, including loan payments. The lifetime extension is considered in the investment algorithm. The actual dismantling year might

the financial results were not fed to the dispatch module, and the weather profiles were not fed to the investment decisions module. However, a disadvantage of the co-simulation was that a large part of the runtime was spent reading and writing to the databases.

[6] Four years is the lead time for hydrogen turbines. Ideally, the market would be tested for each lead time ahead, but to limit the computational effort, we compute only Y + 4.

[7] Another option was to decrease the efficiency, but this would not be possible for VRES, as their generation is dependent on capacity factors.

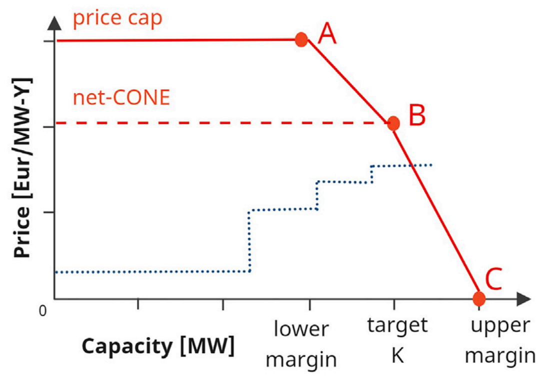


Fig. 2. Sloped demand curve in our simulations considering a centralized capacity market.

differ from the assumed dismantling year at the time of investment due to changes in the generation portfolio and differences between the actual simulated weather and the reference weather year that was used in the investment decision.

3.2. Policy options

This section describes the three capacity remuneration mechanisms considered in our analysis.

3.2.1. Capacity market

Our model of the central capacity market is inspired by the Belgian CM [54]. The capacity demand curve's parameters (Fig. 2) are set as follows. The CONE, which represents the cost of additional firm capacity, is calculated as the sum of the capital and annual fixed costs, adjusted to each technology's derating factor as explained in Art. 15 of the ACER methodology [28]. The fixed costs FC are the annual fixed operating and maintenance costs associated with keeping a plant available for operation. In our simulations, the reference technology is the one with the cheapest CONE. The net-CONE is calculated by subtracting the revenues from the energy-only market from the CONE.[8] For point A, the price corresponds to the price cap, here the maximum of the net-CONE*1.5 and the CONE. At point B, the price is the net-CONE (represented with the slashed line). Finally, the price at point C is zero. Recalculating the price cap based on the net-CONE in each year caused capacity prices to become volatile. Therefore, we only calculate the capacity price cap and the net-CONE in the first simulation year.[9] The capacity at point B is the target capacity. We set capacity at the lower margin A to be 5 % lower than the target capacity and point C to be 5 % higher.

For the supply side of the CM, we assume that companies bid their missing revenues, i.e., the additional revenues they would need to achieve a net positive cash flow in the next year. New generators consider their fixed costs FC, operating expenditures $OPEX$ (which include variable costs and fuel costs), and annualized capital costs (loans L)[10]:

$$\pi_y^{NewPlants} = \sum_{h \in H} p_h \cdot q_h - OPEX_y - FC_y - L_y \qquad \forall y \in Y \tag{1}$$

We model existing generators as price takers that exclude their annualized capital costs from their bids:

$$\pi_y^{ExistingPlants} = \sum_{h \in H} p_h \cdot q_h - OPEX_y - FC_y \qquad \forall y \in Y \tag{2}$$

New and existing generators' CM bids are set to zero if the anticipated wholesale market revenues exceed their total costs.

$$bid_y = \max\left(0, \frac{-\pi_y}{K \cdot DF}\right) \qquad \forall y \in Y \tag{3}$$

We estimate the derating factors (DF) of each technology by the average energy produced during the hours of scarcity and near-scarcity relative to their nameplate capacity in an EOM model run of 40 years, considering the installed capacity at the start of the simulation.[11] We do not model ramping constraints or forced outages, so the DF of dispatchable technologies is equal to 1. We model a pay-as-cleared (PAC) capacity auction with annual contracts that clears 4 years in advance.

3.2.2. Strategic reserve (SR)

In an SR, the generators with the highest operating costs (the oldest ones) are placed in the reserve and removed from the market. The EU regulation states that the price of energy produced by a strategic reserve that is dispatched during a shortage must be at least equal to the VOLL [6].[12] The SR operator (typically, the TSO) retains the market revenues and uses them to offset the cost of contracting the reserve capacity:

$$\pi_y^{SR\ Operator} = \sum_{t \in T^{SR}} \sum_{g} p_t \cdot q_{t,g} - SR_{y,g}^{payments} \qquad \forall y \in Y \quad \forall g \in G^{SR} \tag{4}$$

Power plants in the reserve are paid for their cost of remaining online, which includes their fixed costs, loans (if they have not already been paid off), and the variable costs and fuel costs in case they are activated.

$$SR_{y,g}^{payments} = \sum_{t \in T^{SR}} (OPEX_g \cdot q_{y,t,g}) + FC_{y,g} + L_{y,g} \quad \forall y \in Y \quad \forall g \in G^{SR} \tag{5}$$

In our simulation, plants are eligible to enter the reserve four years before the end of their lifetime. They may stay there for a maximum of ten years (or until their maximum lifetime has been reached). Similar to the German SR, contracted plants remain in the reserve until they are decommissioned. They are not permitted to return to the market once they are no longer contracted. The technologies that may participate in an SR in our model are H_2 turbines and biofuel plants (see Section 4). Partial capacities are not accepted; therefore, an additional marginal amount of capacity may be contracted if required.

Because the SR is contracted 1 year ahead, the investment algorithm does not have information about which plants will be in the reserve in the investment reference year 4 years ahead. For this reason, the investments are made under the assumption that the policy will remain in place and, therefore, the plants that are currently in the reserve will remain in the reserve.

3.2.3. Capacity subscription (CS)

In a market with CS, consumers purchase capacity contracts in a centralized auction. In case of shortages, consumers are limited to their subscribed capacity [51]. This situation is referred to as load limiting (LL). Consumers may choose to subscribe to less capacity than their peak demand if their estimated cost of being limited during scarcity hours is lower than the cost of capacity. Consumer groups are modeled as having a number of load segments with different values of lost load.

In our model, consumers subscribe to capacity for the following year. They choose their subscription levels based on the total share of subscribed consumers and the experienced shortages during the current simulation year. The consumers' bid prices and volumes for capacity are based on their differentiated VOLL (see Table 1) and the duration and

[8] Note we do not account for ancillary market revenues and variable CONE.

[9] During the initialization phase, a lower installed capacity could cause extremely high revenues and a low price cap; therefore, the price cap is exogenous for that simulation phase.

[10] For sake of simplicity, we omit any index referring to companies or technologies.

[11] The near-scarcity hours are those during which DSR is also operational.

[12] The regulation recommends to dispatch at the VOLL or at a higher value than the intraday technical price limit.

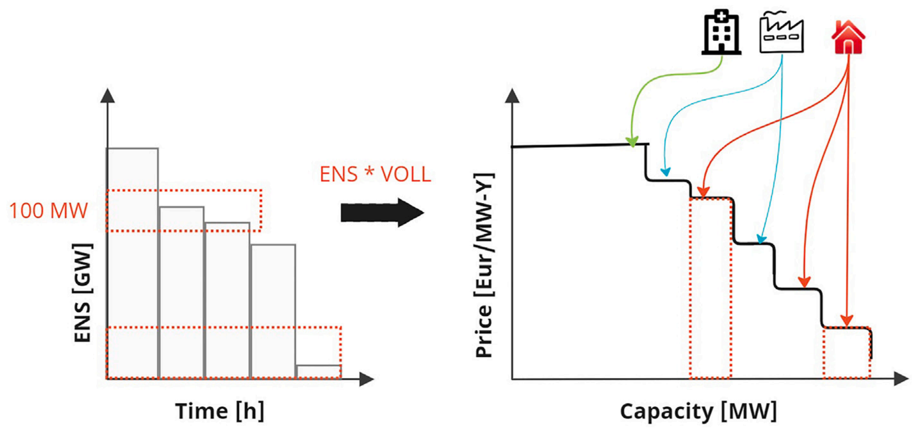


Fig. 3. For each consumer group, the hourly energy not supplied, per blocks of 100 MW, determines the volume-price bids. In this way, we simulate consumer groups assigning different values to parts of their load. For example, households might value lower their EV load. The demand curve is then the aggregation of all consumers' segmented bids.

Table 1
The VOLL of different categories of consumers [58,59].

	VOLL [Eur/MWh]	Load share [%]
Transport	78,082	4
Public sector	75,286	9
Commercial and service sector	56,496	13
Industry, non-energy-intensive	50,618	5
Industry, energy-intensive	44,904	28
Household other	33,635	9
Household city center	28,646	21
Household feed-in areas	27,499	8
Industry SME	19,207	3

The VOLLs in [58] were based on surveys in which respondents were asked to value their reliability supply relative to their total bill costs, and that year, the electricity prices were extraordinarily high. De Nooij et al. [59] determined VOLLs per consumer group through a production function approach. We applied a factor of 1.5 to account for inflation.

depth of the shortage from the dispatch results of the current year, as illustrated in Fig. 3. If the electricity supply is tight, the marginal value of a higher capacity subscription increases, and therefore consumers' bids for capacity increase, as explained below.

First, we calculate the hourly unsubscribed demand per consumer group $D^{unsubscribed}_{CG,h}$ by subtracting the subscribed capacity $K^{subscribed}_{CG}$ from their hourly demand $D_{CG,h}$. This represents the hourly load of each consumer group that can be limited.

$$D^{unsubscribed}_{CG,h} = max(0, D_{CG,h} - K^{subscribed}_{CG}) \quad (6)$$

Next, the probability of being limited $P(LL)_{CG,h}$ is calculated as the share of unsubscribed demand per consumer group relative to the total unsubscribed demand:

$$P(LL)_{CG,h} = \frac{D^{unsubscribed}_{CG,h}}{\sum_{CG} D^{unsubscribed}_{CG,h}} \quad (7)$$

In case of scarcity, the curtailed load is distributed to the consumer groups according to the $P(LL)_{CG,h}$. This assumes that all unsubscribed load is equally likely to be curtailed, hence, in expectation, the energy not served per consumer group reads:

$$ENS_{CG,h} = P(LL)_{CG,h} \cdot ENS_h \quad (8)$$

To determine the bid price for the next capacity contract auction, we start by assessing the value of the current subscription volume $bid\,P_{CG,0}$. We do this by calculating the expected avoided cost of lost load by subscribing to an additional unit of capacity of 1 MW:

$$bid\,P_{CG,0} = \sum_h min(1, ENS_{CG,h}) \cdot VOLL_{CG} \quad (9)$$

This yields the bid price for $bid\,P_{CG,0}$ for the current subscription volume in the next capacity contract auction. Then, we determine the bid price $bid\,P_{CG,b}$ per capacity increment b of 100 MW. To find the value for extra capacity, we determine the expected avoided cost per additional capacity subscription block b of 100 MW as follows:

$$bid\,P_{CG,b} = \sum_h min(max(0, ENS_{CG,h} - (b-1) \cdot 100), b \cdot 100) \cdot VOLL_{CG} \quad (10)$$

Note that this calculation is based on the latest energy-only market results, i.e., it assumes that the ENS does not change. In years without shortages, consumers' marginal value of capacity would hence decrease to zero. For this reason, we apply a minimal bid price of 9000 Eur/MW for the current subscription volume $bid\,P_{CG,0}$. This reflects an assumed awareness among consumers that they must continue purchasing capacity to avoid future shortages. This minimum price is higher than the fixed costs of hydrogen turbines to ensure their continued presence.

Finally, all bid blocks are aggregated into a decreasing stepped demand curve for capacity and the market is cleared as a pay-as-bid auction. Bids below the clearing price are not accepted and bids that are equal to the clearing price might be partially accepted on a pro-rata basis.

On the supply side, generators offer their capacity in the same way that a CM, as explained in Section 3.2.1. However, investors do not have a precise estimate of the CS price at the time of investment because the CS market is cleared one year in advance, and investment decisions are made four years in advance. We assume that agents base their investments on the average CS price over the past three years.[13] In years with high CS prices, generators have strong incentives to invest, but they stop investing if there are enough generators in the investment pipeline to cover the expected demand, plus a margin of 5 % to accommodate the lumpiness of generator investments.

Finally, we run a two-sided pay-as-cleared auction. To ensure that subscribed consumers never experience curtailment of their subscribed demand, only dispatchable technologies that will be operational in year Y+1 are allowed to sell credits.

[13] For the first years of a model run, the average of the available past simulation results is taken.

Table 2
Capacity Market scenarios.

Scenario	Endogen. DF	Target volume [GW]	Participating technologies	Auction time
CM	N	20	H2 turbines, bioenergy, nuclear	Y-4
CM_VRES_BESS	N	26.5	PV, wind, BESS, H2 turbines, bioenergy, nuclear	Y-4
CM_VRES_BESS_lowTV	N	24.5	PV, wind, BESS, H2 turbines, bioenergy, nuclear	Y-4
CM_endogen_lowTV	Y	24.5	PV, wind, BESS, H2 turbines, bioenergy, nuclear	Y-4

Table 3
Strategic Reserve scenarios.

	DSR	Activation price	Margin %	Participating technologies	Selection time
SR	Y	4000	10	H2 turbines, bioenergy	Y-1
SR_noDSR	N	4000	10	H2 turbines, bioenergy	Y-1

4. Case study

In this section, we first describe the data used, then describe the design of our model experiments, and finally, we describe the indicators used to assess the performance of the policy options.

4.1. Data

4.1.1. Technologies

We consider only carbon-free technologies. These include hydrogen-fueled open-cycle gas turbines (H_2-OCGT) and closed-cycle gas turbines (H_2-CCGT), wind onshore, wind offshore, lithium-ion batteries with energy-to-power ratios of 2 and 4 h, photovoltaic (PV) systems, and biofuel. Based on [55], we consider H_2-fueled turbines. However, other options, like turbines fueled by synfuels, biogas, etc., would perform similarly [13]. For all technologies, the equity interest rate is 7 % and the debt-to-equity ratio is 80 %. The debt-interest rates are distinguished by technology. The technology costs and fuel prices are obtained from the TradeRES database [56] (see Tables 9 and 11).

To assess the impact of weather variability on the reliability of the power system, we calculate capacity factor profiles per technology, considering technological advancements, as described in [1].

4.1.2. Initial power plant portfolio

We take the initial power plant set from the output of the optimization model COMPETES [7], which is a reference model for Dutch energy policy. We use the output of a model run without cross-border transmission capacity as shown in Table 9. We assume that one existing nuclear plant, Borssele (with a capacity of 484 MW), will remain operational rather than being decommissioned in 2033.

4.1.3. Load

The capacity of electrolyzers and industrial heating demand are also derived from COMPETES. In contrast to this co-simulation, COMPETES simulates sector coupling; the flexibility of industrial heating stems from the possibility of switching to gas boilers when the price of electricity is high. AMIRIS can model one type of load-shifter, and because industrial heat is the largest flexible demand source, we model this load as the load-shifter with a price-cap. Its maximum willingness to pay corresponds to the natural gas price factored with the CO_2 price. The annual demand from the industrial load shifter was 36,757 GWh, with a peak consumption of 6155 MW, and the installed capacity of electrolyzers was 37,450 MW. The electricity demand of the electrolyzers is modeled as a load-shedder, the production of which is interrupted if the electricity price is higher than the opportunity cost of the hydrogen market price (corrected for the electrolyzers' conversion efficiency).

Because AMIRIS currently only facilitates one load shifter agent, we consider heat pumps (HP) and electric vehicles (EV) as static loads, even though, in reality, these technologies may provide significant flexibility [57]. We augment historical demand profiles with the projected amount of HPs and account for the correlation with temperature (see [1]).

We consider the average of two studies on the Value of Lost Load (VOLL) of consumers in NL. See Table 1. We assume that in the future, 11 % of consumers, the ones with the lowest VOLL (household feed-in areas and industry SMEs) will be able to offer DSR, meaning they will have a VOLL of 1500 Eur/MWh, which is lower than the power exchange price cap. In this publication, we refer to this load as DSR.

4.2. Experiment design

We evaluate the performance of a capacity market, a strategic reserve, and capacity subscription, subject to weather uncertainty, with an EOM as a reference. After comparing some variations within each mechanism, we compared one scenario of each mechanism, which are denoted in bold letters in the following Tables 2, 3, and 4. To make the CRMs comparable, we sized them so that the involuntary load shedding was reduced to a similar level.

We compare a case in which only dispatchable technologies (nuclear, H_2 turbines, biofuel) are allowed to participate in the capacity market (Scenario 'CM', Table 2) with a scenario in which BESS and VRES may also participate ('CM_VRES_BESS'), following the recommendation in EU regulation Art. 22 of [6] about technology-neutral CRMs. We calculated the target capacity from the average peak load during the top 4 h of scarcity in an EOM simulation of 40 weather years. For the CM scenario, the target capacity is reduced by the derated initial installed capacity of the non-participating technologies. Additionally, we evaluate a lower target volume (TV) for the CM with VREs and BESS ('CM_VRES_BESS_lowTV') because, with a volume of 26.5, the shortages were reduced to zero hours in most years, which indicates that the CM was oversized.

In the CM_VRES_BESS scenario, the derating factor (DF) is calculated before the simulations. We also test a scenario in which the DFs are endogenous ('CM_endogen_lowTV'). In the latter case, we recalculate the DF during the simulation based on the availability of each technology in scarcity and near-scarcity hours, using the outcome of a market simulation for Y + 4 considering a median weather year (see Section 3.2.1). We reset the new value to the average of the past 4 years, omitting the DFs of years in which there are no near-scarcities.[14] Table 2 presents an overview of the CM scenarios.

For the basic SR scenarios, we set the SR activation price to 4000 Eur/MWh, which is equal to the day-ahead price cap. The EU regulation states that during periods when the SR is dispatched, the imbalances in the market are to be settled at a price level that is at least equal to the VOLL [6]. The SR volume is calculated using the highest forecasted non-flexible demand of a median weather year times a margin of 10 %. We selected this margin because it resulted in a LOLE similar to the other CRMs, allowing us to compare the CRMs.

[14] In years with a slight excess capacity with no shortages, DF would be zero, which would ignore the potential contribution of technologies during scarcity.

Table 4
Capacity Subscription scenarios.

	Memory	Min. price	RO	Participating technologies	Auction time
CS	Y	Y	N	H2 turbines, bioenergy, nuclear	Y-1
CS_RO	Y	Y	Y	H2 turbines, bioenergy, nuclear	Y-1
CS_noMinPrice	Y	N	N	H2 turbines, bioenergy, nuclear	Y-1
CS_noMemory	N	Y	N	H2 turbines, bioenergy, nuclear	Y-1

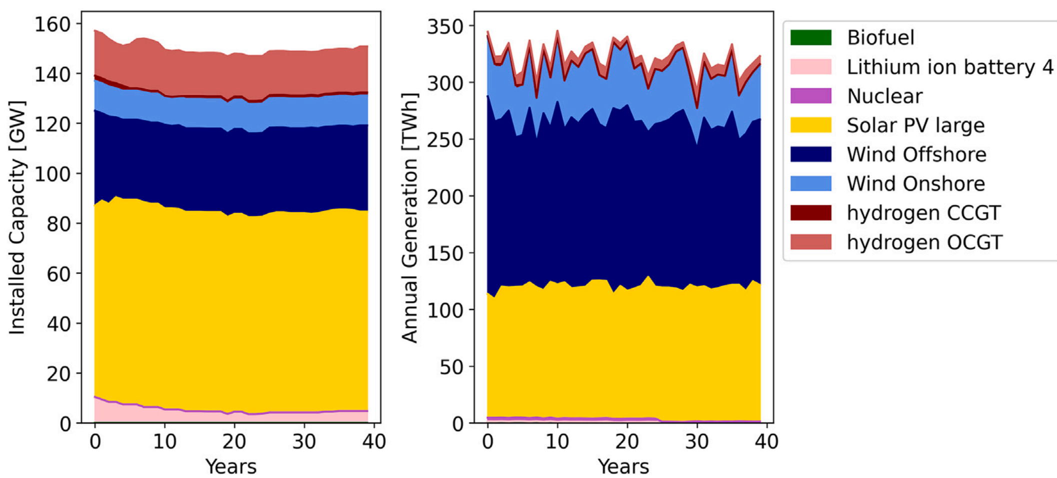


Fig. 4. Left: Installed capacity per technology in an EOM. Solar energy was the technology with the highest installed capacity. Right: Annual generation per technology in EOM. The annual production of wind energy was volatile year-to-year.

We conduct a sensitivity analysis in which there is no DSR at a lower price than VOLL (SR_noDSR). In an SR, only H_2 turbines and biofuel are allowed to enter the reserve. Table 3 indicates the availability of DSR, the activation price of the SR, the capacity margin (share) that is provided by the SR, the technologies that are contracted in the SR and the time when plants are selected to participate in the SR.

In our study of CS, we compare a simple CS design with one in which generators that sell capacity have a clawback when the prices in the wholesale market are above a strike price, in other words, a CS with reliability option (CS_RO). In this way, the payback reduces the costs to consumers and the revenues for generators. We implement a strike price of 150 Eur/MWh, following the recommendation to set the strike price at least 25 % above the most expensive generator [60].

We assume that generators consider the past three annual CS prices for their investment decisions and that consumers offer the average of the current simulation year' bid (as explained in Section 3.2.3) and the bids from the past three years. We test a scenario where neither consumers nor generators consider the past results (CS_noMemory). Finally, we investigate a scenario in which consumers do not submit offers with a minimum price (CS_noMinPrice). For an overview of the considered scenarios, see Table 4.

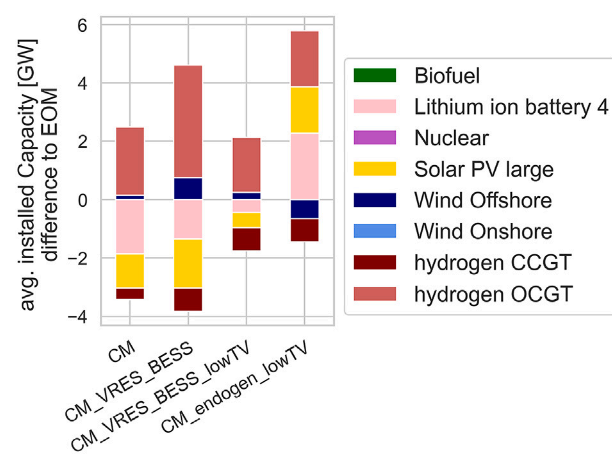


Fig. 5. Difference in the average installed capacity over the last 10 simulation years between the CM scenarios and an EOM. In all CM scenarios, the installed capacity of H_2-turbines increased.

4.3. Key performance indicators (KPIs)

The policy objective for the tested market designs is to achieve a sustainable, secure, and affordable power system. Because we do not consider fossil-fueled technologies, we do not include environmental indicators and only consider adequacy and financial indicators. In this section, we describe the indicators that we use to compare the CRMs.

- Adequacy-related KPIs
  - Energy Not Served (ENS) (MWh/year): Load that cannot be served. We distinguish between voluntary shedding (DSR) (Section 4.1.3), and involuntary shedding, to which we refer as load shedding (LS).
  - Loss Of Load Expectation (LOLE) (hours/year): number of hours during which resources are insufficient to meet the demand.[15]
  - Hydrogen production (MWh): Power consumed by electrolyzers to produce hydrogen.
- Financial KPIs:
  - Weighted averaged yearly electricity prices (Eur/MWh):

$$\overline{p_y} = \frac{\sum_h^H p_h \cdot q_h}{\sum_h^H q_h} \tag{11}$$

[15] The demand of electrolyzers and DSR is modeled as a load shedder, but this is not counted as ENS or LOLE.

Table 5
Capacity market average ($\overline{x}$) and standard deviation (σ) results. In CM_VRES_BESS scenario all technologies participated, in CM_VRES_BESS_lowTV, the target volume was smaller, and in CM_endogen_lowTV the DFs were calculated endogenously.

		EOM	CM	CM_VRES_BESS	CM_VRES_BESS_lowTV	CM_endogen_lowTV
ENS [MWh]	$\overline{x}$	6375	2268	867	5500	3650
	σ	7577	3909	2579	15,797	8950
LOLE [h]	$\overline{x}$	4.23	1.85	0.68	3.40	2.48
	σ	4.77	2.55	1.90	6.97	4.78
Weighted average electricity prices [Eur/MWh]	$\overline{x}$	38.53	37.52	36.73	37.96	37.53
	σ	4.47	3.80	3.38	4.57	4.21
Cost recovery [%]	$\overline{x}$	120.71	121.26	122.13	123.40	123.16
	σ	8.26	6.87	6.73	9.29	8.15
Weighted average CRM Costs [Eur/MWh]	$\overline{x}$	0.00	1.00	2.25	1.51	1.91
	σ	0.00	0.59	1.14	0.69	0.85
Cost to consumers [Eur/MWh]	$\overline{x}$	38.53	38.52	38.98	39.47	39.43
	σ	4.47	3.88	3.72	4.65	4.34
Total system costs [mln. Eur]	$\overline{x}$	10,543	10,302	10,320	10,539	10,445
	σ	711	653	602	959	754
CRM costs [mln. Eur]	$\overline{x}$	0	321	721	484	610
	σ	0	188	361	219	265

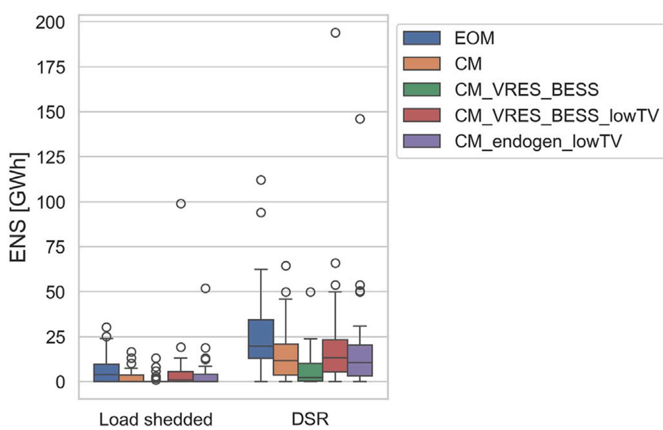


Fig. 6. ENS was reduced in all CM scenarios. Allowing BESS and VREs to participate in a CM with a lower target volume led to high ENS volumes in years with low VREs.

- Total CRM Costs (Eur), in which p_y^{CRM} is the CRM clearing price:

$$C_y^{CRM} = p_y^{CRM} \cdot q_{y,g} \qquad \forall g \in G^{CRM} \tag{12}$$

- Cost recovery (%):

$$CR_y = \frac{p_y \cdot q_y + C_y^{CRM}}{\sum_g (OPEX_y + FC_y + L_y + DP_y)} \qquad \forall g \in G \tag{13}$$

The loans L are calculated with the debt-to-equity ratio D/E, the expected lifetime T_{EL}, and the interest rate per technology i

$$L_y = \frac{CAPEX \cdot D/E}{\frac{1}{i}\left(1 - \frac{1}{(1+i)^{T}\mathrm{EL}}\right)} \tag{14}$$

The downpayments DP are considered to be paid during the construction years T_C.

$$DP_y = \frac{CAPEX \cdot (1 - D/E)}{T_C} \tag{15}$$

- Weighted average CRM Costs (Eur/MWh):

$$\overline{p_y^{CRM}} = \frac{C_y^{CRM}}{\sum_h^H q_h} \tag{16}$$

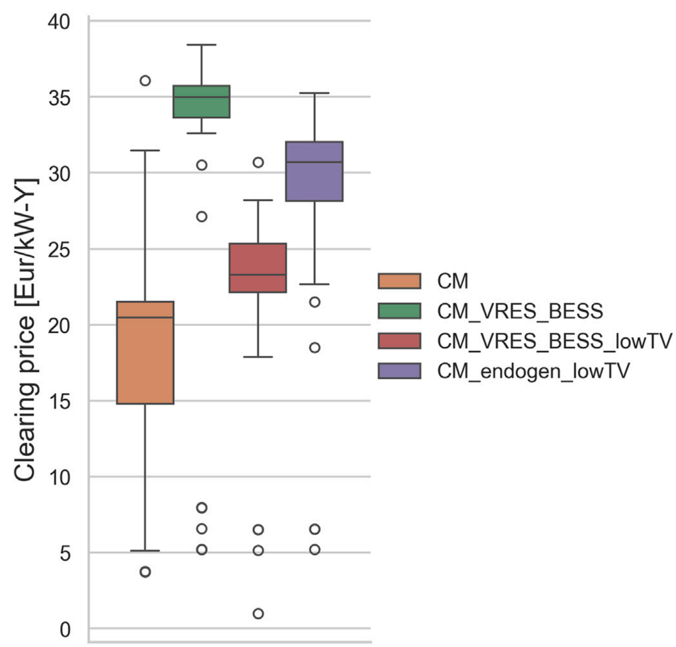


Fig. 7. Capacity market prices were constantly higher if it was oversized.

- Cost to consumers (Eur/MWh): This is the weighted average payments by consumers for electricity supply including their expenditures on a CRM, if applicable.

$$C_y^{consumers} = \overline{p_y} + \overline{p_y^{CRM}} \tag{17}$$

- Total system costs (Eur):

$$C_y^{society} = \sum_g (VC_y + FC_y + L_y + DP_y) + ENS_y \cdot \overline{VOLL} \qquad \forall g \in G \tag{18}$$

The total system costs represent the total cost of generation plus the cost to consumers for any unserved energy. Here, the $\overline{VOLL}$ is the weighted average VOLL over all consumer groups in Table 1. For CS, $\overline{VOLL}$ is the weighted average VOLL of unsubscribed demand sections.

- Normalized annual NPV (Eur):

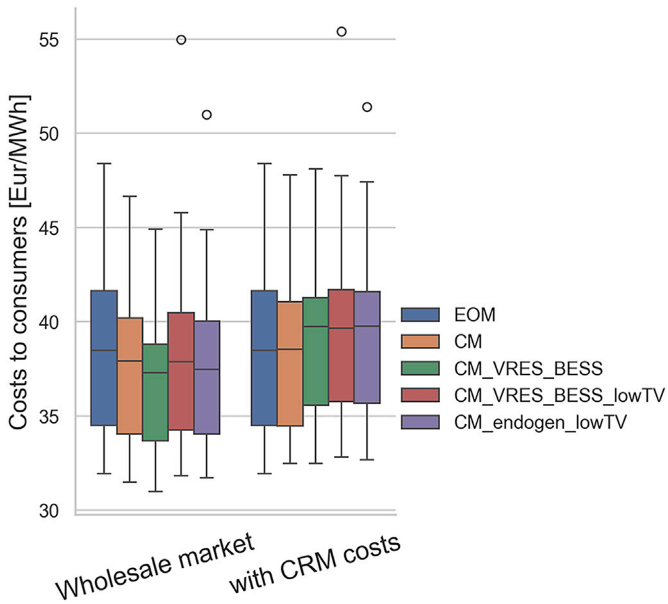


Fig. 8. Capacity market reduced wholesale market prices but adding up the capacity costs, the yearly costs to consumers were higher than an EOM, except in CM scenario.

The annual NPV is calculated assuming that revenues and costs remain constant for each operational year.

$$CashFlow_y = \begin{cases} -DP_y & \text{for} \quad 0 \geq y \geq T_C \\ p_y \cdot q_y + C_y^{CRM} - FC_y - VC_y - L_y & \text{for} \quad T_C > y \geq T_C + T_{EL} \end{cases} \tag{19}$$

The debt interest rate ρ was the same for all technologies

$$NPV_y = \sum \frac{CashFlow_y}{(1+\rho)^y} \tag{20}$$

For the normalized annual $nNPV$ the capacity of the generator K is considered

$$nNPV_y = \frac{NPV_y}{K} \tag{21}$$

5. Results

We present the results of an EOM as a reference case and compare them to an electricity market with a CM, with an SR, and with CS. At the end of this section, we present a comparison of these mechanisms.

5.1. Energy-only market (Reference case)

In the EOM simulation, the LOLE was above 4 h for 26 years, 4.23 h on average. The average electricity price was 38.53 Eur/MWh and the average investment cost recovery was 120 %. In all simulations, onshore wind was the most profitable technology, and it always reached its physical limit. Fig. 4 shows that although PV was the technology with the largest installed capacity, most energy was produced by offshore wind. The annual output of the dispatchable technologies varies significantly as a result of the differences in the availability of wind and solar energy in each weather year. The dispatchable technologies had the lowest returns on investment. In the last years of the simulation, the installed capacity of batteries was 4.8 GW. This decrease with respect to the initial capacity of 21 GW can be explained because we apply a conservative storage dispatch strategy (Section 3.1.1) and because we do not model ramping constraints on competing dispatchable technologies or ancillary services markets, reducing the profitability of BESS.

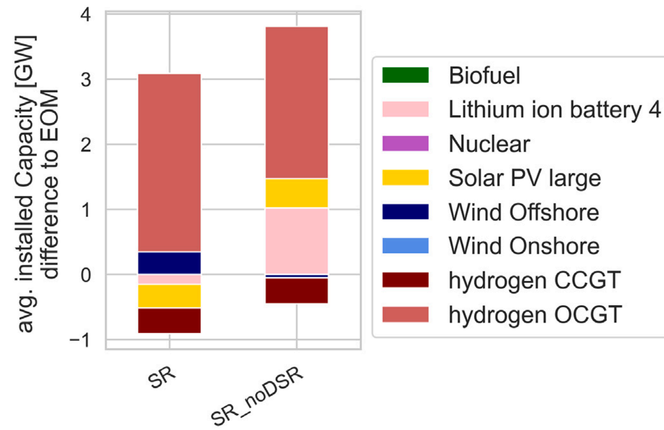


Fig. 9. Average difference of installed capacity in 10 last simulation years with SR scenarios. Without DSR prices were more volatile which incentivized more batteries.

Table 6
SR results.

		EOM	SR	SR_noDSR
ENS [MWh]	$\bar{x}$	6375	2992	8129
	σ	7577	5157	11,103
LOLE [h]	$\bar{x}$	4.23	2.30	10.83
	σ	4.77	3.29	9.47
Weighted average electricity prices [Eur/MWh]	$\bar{x}$	38.53	42.92	46.60
	σ	4.47	8.02	8.53
Cost recovery [%]	$\bar{x}$	120.71	136.75	148.89
	σ	8.26	19.66	22.08
Weighted average CRM Costs [Eur/MWh]	$\bar{x}$	0.00	0.74	0.78
	σ	0.00	0.37	0.38
Cost to consumers [Eur/MWh]	$\bar{x}$	38.53	42.96	46.17
	σ	4.47	7.49	7.82
Total system costs [mln. Eur]	$\bar{x}$	10,543	10,466	10,368
	σ	711	700	672
CRM costs [mln. Eur]	$\bar{x}$	0	235	249
	σ	0	112	115

5.2. Results: capacity market

In a CM that awarded only dispatchable technologies, most CM payments went to H_2-OCGT plants. Hence, more H_2-OCGT capacity and, remarkably, wind offshore was installed (2.6 GW) compared to an EOM. The BESS and PV capacity, which didn't receive CRM payments, was reduced by 3 GW. A similar effect was observed even if VREs and BESS were awarded due to their low DFs. Nevertheless, their capacity was reduced in a lower proportion than the increase in H_2-OCGT (see Fig. 5). For the scenario where DFs were calculated ex-ante, the BESS with an E-P ratio of 4 h resulted in a DF of 25 %, and the ones of 2 h a DF of 11 %. Wind offshore and onshore DF were 6 and 12 % respectively, while the DF of PV was 0. In the simulation where the DF were calculated endogenously, CM_endogen_low_TV, we observed an initial overshoot in the DF of BESS and a stable value after 15 years, at 45 %. The DF of wind offshore decreased to almost 0 %, and less of this technology was installed. BESS capacity facilitated higher utilization and capture prices of solar energy, and therefore both technologies either reduced or increased in the same direction. In other words, although there were no capacity payments for PV, more of this technology was installed when BESS capacity increased.

A CM helped reduce shortages in all scenarios. In scenario CM_VRES_BESS, considering a target volume of 26.5 GW, the LOLE was reduced to 0.6 h/Y. Considering a lower target volume of 24.5 GW, the LOLE was 3.4 h/Y (see Table 5). With a lower target volume, the shortages in the scenarios that awarded VRES and BESS were at a similar level

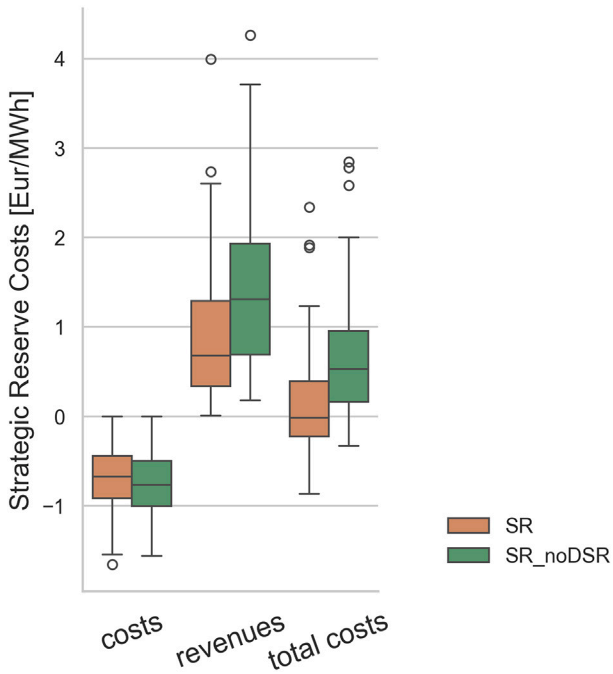


Fig. 10. Adding up yearly costs and surplus revenues from power plants in the strategic reserve, the extra costs were almost 0 Eur/MWh.

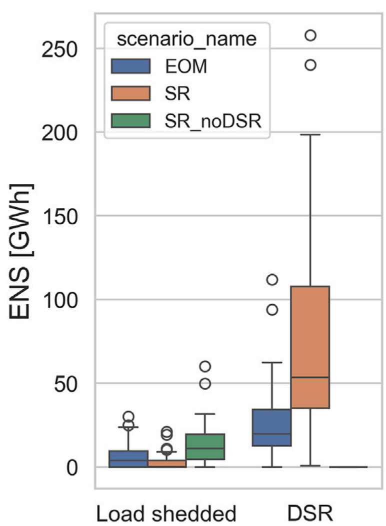


Fig. 11. In an SR_noDSR the involuntary load shedded was higher because there was no DSR activation.

as the CM where only dispatchable technologies participated. However, in one year, there was a very high shortage of almost 100 GWh (higher than with an EOM), as shown in Fig. 6, illustrating the risk of estimating the DF of VREs and BESS based on average performance that may hide very poor performance in extreme years.

Fig. 7 shows that CM prices were very volatile, which may be attributed to the myopic nature of investment decisions, imperfect foresight, and the lumpiness of investments. The investor agent lacks a precise assessment of the decommissioning year of the power plants. Higher or lower profitability than anticipated could lead to the decommissioning of certain units earlier or later than economically optimal. During years with lower available capacity, new H_2-turbines set the capacity price. In contrast, during years with a surplus of installed capacity (with respect to the capacity target), existing power plants set the price.

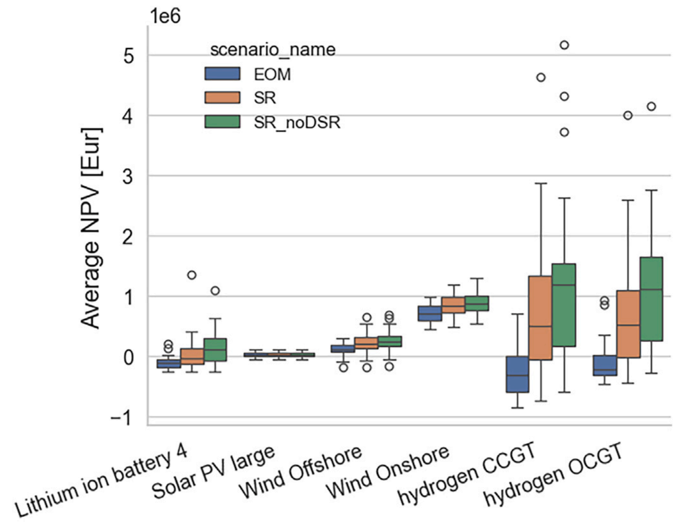


Fig. 12. Annual normalized NPV by technology in SR scenarios.

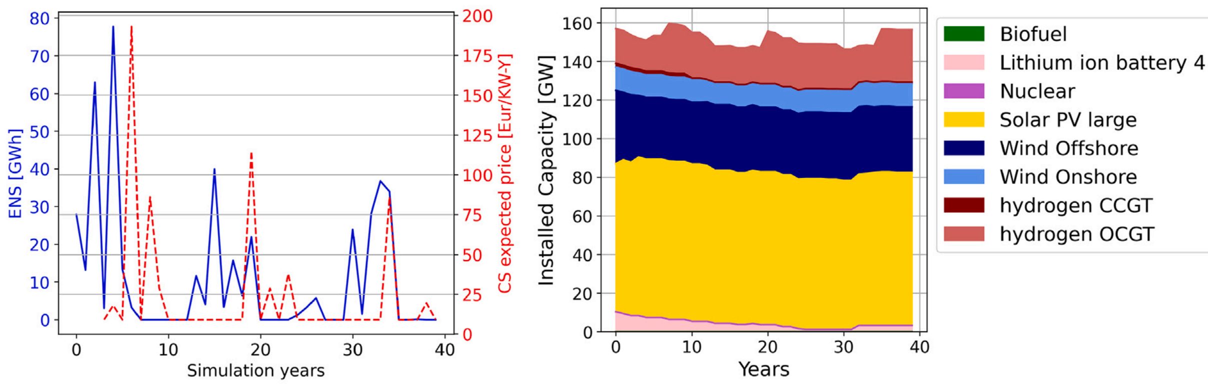
If the capacity target was oversized, then the prices were constantly higher because new turbines set the price in most years; this was the case in CM_VRES_BESS scenario.

Due to the reduction of scarcity prices, wholesale market prices were also reduced, as shown in Fig. 8. Adding expenses in the EOM and the CRM payments, the total costs to consumers were higher than in an EOM, except for the CM scenario. In contrast, in all CM scenarios, as shown in Table 5, the total system costs were lower than in an EOM. This is due to the reduction of ENS. However, in the CM_VRES_BESS_lowTV scenario, there was one year with a high shortage, which led to total system costs of more than 15.2 bn (compared to 10.5 bn on average), which reflects the danger of outliers and relying on average DFs to value intermittent sources and BESS in a capacity market.

5.3. Results: strategic reserve

Due to the introduction of the SR, the lifetime of the H_2 turbines was extended to the maximum. Hence, investments in new H_2 turbines were delayed, and the cost recovery increased. We observed an increase of 3 GW in H_2-OCGT and offshore investments, as shown in Fig. 9. This is similar to the size of the reserve (3.2 GW). Due to the lumpiness of investments in power plants, the reserve volume was 4 GW in most years. In some years, there were not enough old power plants available to enter the reserve, and the reserve volume decreased to 2 GW. Fig. 10 presents the costs of keeping plants in reserve and the surplus revenues from a high SR activation price (difference between the market price and the variable costs) of these assets. Adding costs and surplus revenues, the total costs of maintaining the plants in reserve were zero in most years.

More capacity in SR led to similar reliability compared to CM but resulted in much higher costs to consumers due to higher and more volatile electricity prices. On average, electricity prices were 4.39 Eur/MWh higher in SR than in an EOM, and in SR_noDSR 8.06 Eur/MWh higher. Although a higher installed capacity reduced the involuntary LS to an average of 2.3 h (SR scenario, Fig. 11), the DSR activation was, on average, 2.8 times higher than in the EOM scenario. This is because the SR activation price (4000 Eur/MWh) was higher than the DSR price (1500 Eur/MWh). As a result, the power plants in the SR were only activated after the DSR volume was fully exhausted. Higher electricity prices resulted in higher revenues for all technologies, especially for dispatchable technologies. H_2 turbines' lifetime was also extended, which caused an increase in their profitability, as illustrated in Fig. 12. In a market without DSR (SR_noDSR scenario), the number of activation hours of plants in the reserve increased from 12.2 to 26.9 h, and the LOLE increased from 2.3 to 10.85 h/Y. More volatile and higher electricity



(a) ENS and expected CS price **(b)** Investment cycles can be observed on the installed capacity of H_2-OCGT

Fig. 13. In CS_noMemory scenario, the investment cycles were remarkable because both the investments and the WTP of consumers changed drastically. Note that the CS price was smoother in the other scenarios where the consumers and investors accounted for the results of the last 3 years.

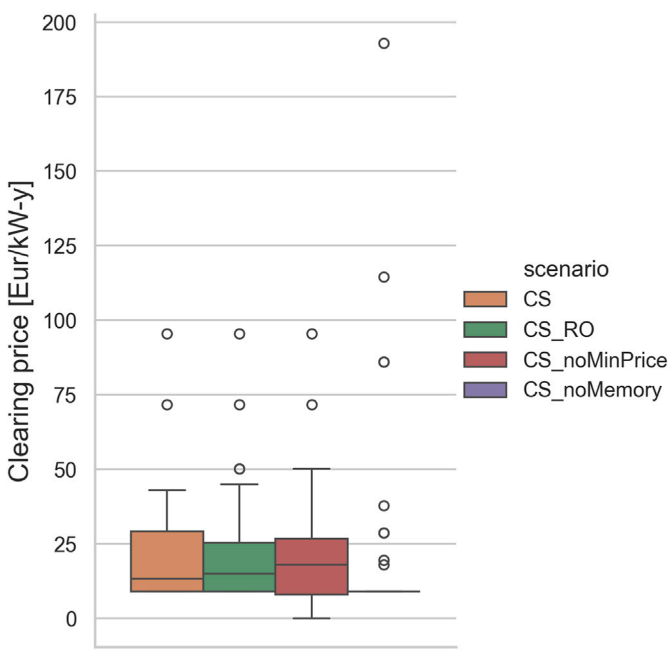


Fig. 14. Yearly CS clearing price.

prices incentivized more batteries and solar energy, as shown in Fig. 9. Due to the fewer involuntary shortages, the SR_noDSR scenario presented lower total system costs than an SR with DSR. However, that scenario presented the highest costs to consumers, as shown in Table 6. We also tested an SR with the same reserve margin and a lower activation price than the DSR (<1500 Eur/MWh) and observed that this may worsen the returns of peak-load plants and of plants that are not in reserve, reducing the investment incentives and increasing the shortages. This occurred as a result of the SR plants activating earlier than the DSR, which decreased wholesale market prices during periods of scarcity.

5.4. Results: capacity subscription

Capacity subscription led to investment cycles (see, e.g., the installed capacity of H_2-OCGT in Fig. 13b). This is because consumers' bids were based on their expected ENS during shortage hours in the preceding years. The investments were reflected in increased generation capacity only after four years. More capacity reduced the shortages, which decreased the willingness to pay (WTP) for capacity. This resulted in

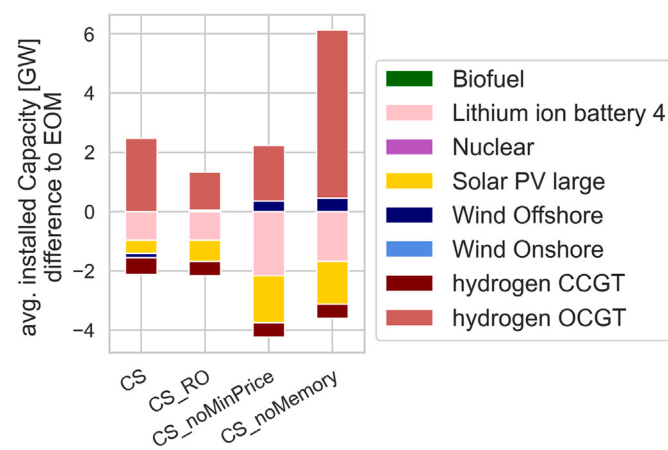


Fig. 15. Difference in the average installed capacity in 10 last simulation years between the CS scenarios and an EOM.

periods of low CS prices and, subsequently, a decrease in investments, leading to more shortages. Fig. 13a shows how, following years of shortages, the expected CS price peaks with a delay.

The WTP increased substantially following years of severe shortages, resulting in extremely high CS prices. CS_noMemory was the scenario with the highest capacity price volatility, as shown in Fig. 14, and with the most volatile profitability for H_2 turbines, as shown in Fig. 18. This indicates that the stability of the capacity price depends on the degree to which consumers consider the risk of shortages. The high CS prices in CS_noMemory incentivized the highest investments, as shown in Fig. 15, and fewer shortages. However, as shown in Table 7, the total system costs were also the highest in that scenario.

An issue with a CS is that consumers may decrease their WTP to a level that would be insufficient for generators to invest or maintain the plants in operation. Introducing a minimal price resulted in a more stable CS volume. However, the CS costs were similar to those of a CS without a minimum price.

If a clawback is implemented, the mechanism can provide price stability to subscribed consumers in a market-compatible manner.[16] A

[16] While CS promotes more dispatchable capacity, the original design doesn't shield consumers from high electricity prices [46]. Ensuring sufficient capacity does not translate into price protection for consumers because a shock in fuel prices or high-price imports can still occur.

Table 7
CS results.

		EOM	CS	CS_RO	CS_noMinPrice	CS_noMemory
ENS [MWh]	$\bar{x}$	6375	3279	3998	3220	1802
	σ	7577	5059	5802	4687	3843
LOLE [h]	$\bar{x}$	4.23	2.33	2.63	2.40	1.23
	σ	4.77	3.41	3.47	2.83	2.49
Weighted average electricity prices [MWh]	$\bar{x}$	38.53	37.56	37.79	37.70	37.02
	σ	4.47	3.74	3.91	3.79	3.50
Cost recovery [%]	$\bar{x}$	120.71	120.92	113.83	121.08	118.60
	σ	8.26	8.27	4.83	7.44	7.57
Weighted average CRM Costs [Eur/MWh]	$\bar{x}$	0.00	1.27	−0.02	1.20	1.41
	σ	0.00	1.13	1.41	1.20	2.20
Cost to consumers [Eur/MWh]	$\bar{x}$	38.53	38.83	37.77	38.90	38.44
	σ	4.47	4.10	3.39	4.10	3.81
Total system costs [mln. Eur]	$\bar{x}$	10,543	10,458	10,495	10,464	10,461
	σ	711	649	669	666	609
CRM costs [mln. Eur]	$\bar{x}$	0	406	−1	384	457
	σ	0	363	452	384	712

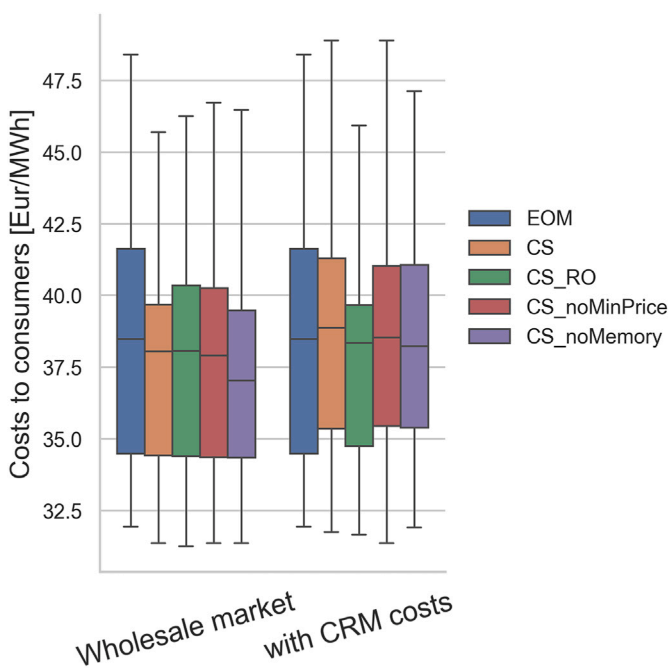


Fig. 16. Yearly costs to Consumers in CS scenarios.

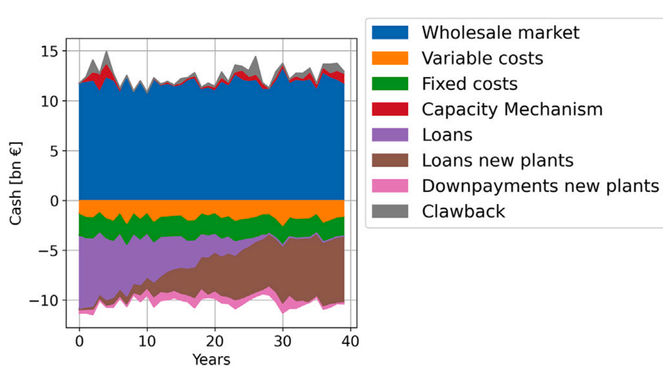


Fig. 17. Cash flows in CS_RO scenario.

clawback reduced cost recovery for generators by 7 %, as shown in Table 7, and lowered the costs to consumers by 1 Eur/MWh, as shown in Fig. 16. Furthermore, it reduced the windfall profits of plants that

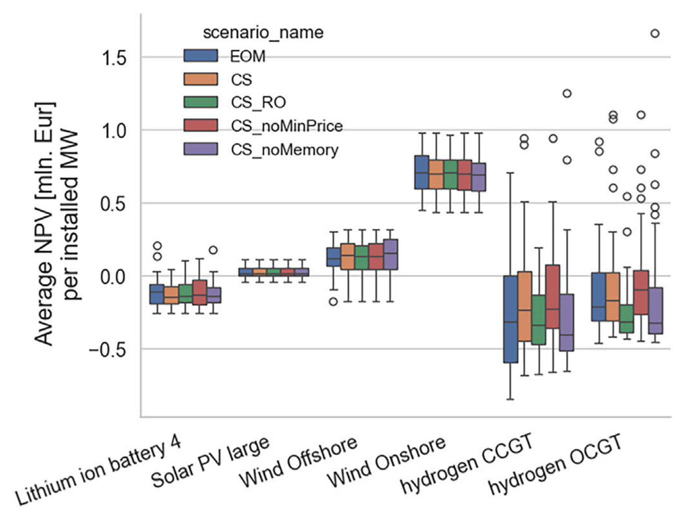


Fig. 18. Annual normalized NPV by technology in CS scenarios.

had already recovered their fixed costs, and in some years, the returned clawback was higher than the CM costs (Fig. 17).

5.5. Comparison of the CRMs

In this section, we compare the following scenarios, an EOM, a CS, a CM without VREs and batteries (to be comparable with CS), and an SR. Fig. 19 shows that all CRMs accomplished the main goal of reducing shortages to a similar level. However, an SR caused higher DSR activation since the plants in reserve became active only after the DSR. As depicted in Fig. 20, the yearly installed capacity of dispatchable technologies was most stable with a CM. This was the reason for CM presenting the lowest shortages. Lower voluntary and involuntary curtailment led to lower total system costs, which were the lowest with a CM (see Fig. 21). The lack of a long-term investment signal is an issue with CS and SR.

Fig. 21 illustrates that both a CS and a CM reduced the volatility and the median electricity price across the different years. Costs to consumers under CS and CM differ by at most 0.3 EUR/MWh w.r.t. EOM, indicating that the reduction in shortages was offset by higher payments to generators. In contrast, an SR increased the cost to consumers by 5.13 Eur/MWh, which increased generator cost recovery on average by 16.04 %. The increased price volatility in SR incentivised more H_2 turbines and increased the profitability of BESS, which were able to exercise energy storage arbitrage. With CM and CS, the profitability

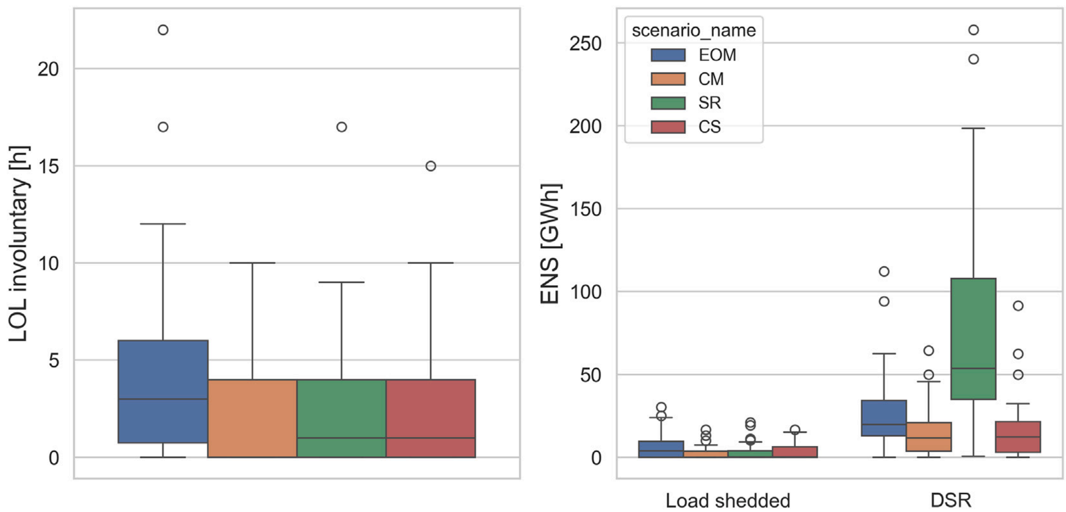


Fig. 19. LOLE and ENS by CRM. The mechanisms reduced the shortages to a similar LOLE and ENS. However, the activation of the DSR was much higher in an SR.

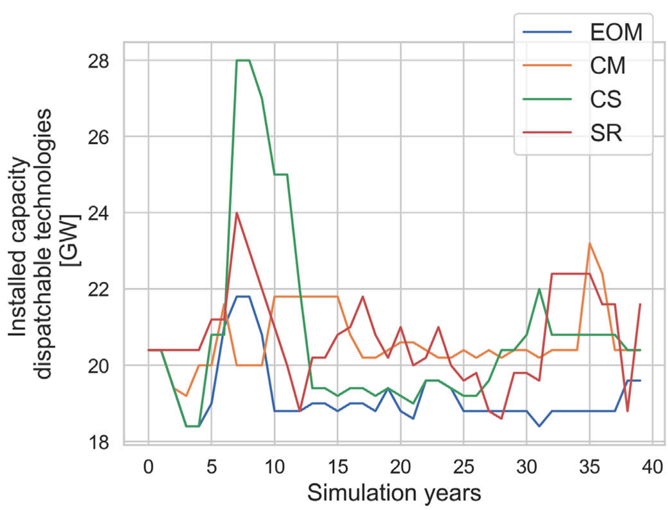


Fig. 20. Yearly installed capacity of dispatchable technologies which include nuclear, bioenergy, and H_2 turbines.

of H_2-OCGT improved and became more stable, but the profitability of BESS decreased, which reduced their installed capacity as shown in Figs. 22 and 23.

Table 8 summarizes a qualitative comparison of the three mechanisms. A CM reduces at most the shortages and the total system costs. Electricity price volatility increases with an SR but is reduced with a CM and a CS. Low volatile prices keep the costs to consumers in CM and CS at a similar level as an EOM, and this can be even lower if a clawback is implemented. In an SR, the volatile electricity prices can incentivize more DSR. However, in an SR, investors rely on scarcity prices and, therefore, don't increase their revenue certainty. Revenue certainty is higher with CS because there are extra payments for capacity. Nevertheless, the price is not guaranteed. Hence, the CM is also the mechanism that increases at most the certainty for investors. If CM payments are awarded with long-term contracts, the investor's certainty can increase even more (we did not model this). Nevertheless, CS is the mechanism that can best avoid a wrong parametrization because it can self-regulate the target volume.

6. Discussion

In this section, we elaborate on some of the strengths and weaknesses of the modeled capacity remuneration mechanisms. The success of capacity markets and strategic reserves depends on difficult parametrization questions. These are less of a problem with capacity subscription, but this faces other implementation issues, such as the possibility of consumers underestimating the risk of scarcity events and the resulting investment cycles.

6.1. Capacity market

One of the main challenges of a capacity market is its accurate parametrization. The price cap of the demand curve is typically determined with the CONE and the net-CONE, which can become volatile. Our analysis did not consider the revenues from balancing and ancillary services, or their option value (extrinsic value), which can be higher for dispatchable technologies [61]. Furthermore, we assumed that fuel prices would remain constant; however, fuel prices could increase fluctuations in the wholesale market revenues.[17] In many European markets, the CONE is set by DSR, which has very broad values ranging from 7500 Eur/MW to 60,000 Eur/MW [2]. Giving a range at which the price cap can vary, as it is in some European countries, could avoid volatile capacity prices.

Similarly, the regulator needs to parametrize the potential contribution to adequacy per technology, a task that is increasingly challenging due to the growing flexibility of demand. The net contribution of each technology depends, among other factors, on the weather, which makes estimating the derating factors (DF) a nearly impossible task and prone to self-fulfilling or self-destroying parametrization [31]. In practice, cyclical variations in DFs, similar to the ones we observed with BESS, may occur. Even if only dispatchable technologies can participate in a CM, to determine the expected residual demand, it is important – but challenging – to consider the contribution of ineligible or opt-out, but operational power plants.

Additional complexity may occur in case an RO is implemented, as Mastropietro explains that participating power plants would factor in the probability of incurring penalties for unavailability during scarcity periods [38]. Because the function of a CRM is to provide reliability and the issue exists when VREs are not available, it appears to be better to remunerate VREs, if necessary, not via a CRM, but through well-designed contracts for differences (CFDs) which do not distort short-term market signals and investment decisions [62,63].

[17] Moreover, fuel price changes would affect the revenues of VREs and hydrogen generators differently, resulting in plants being decommissioned sooner or later than anticipated, complicating the sizing of the CM.

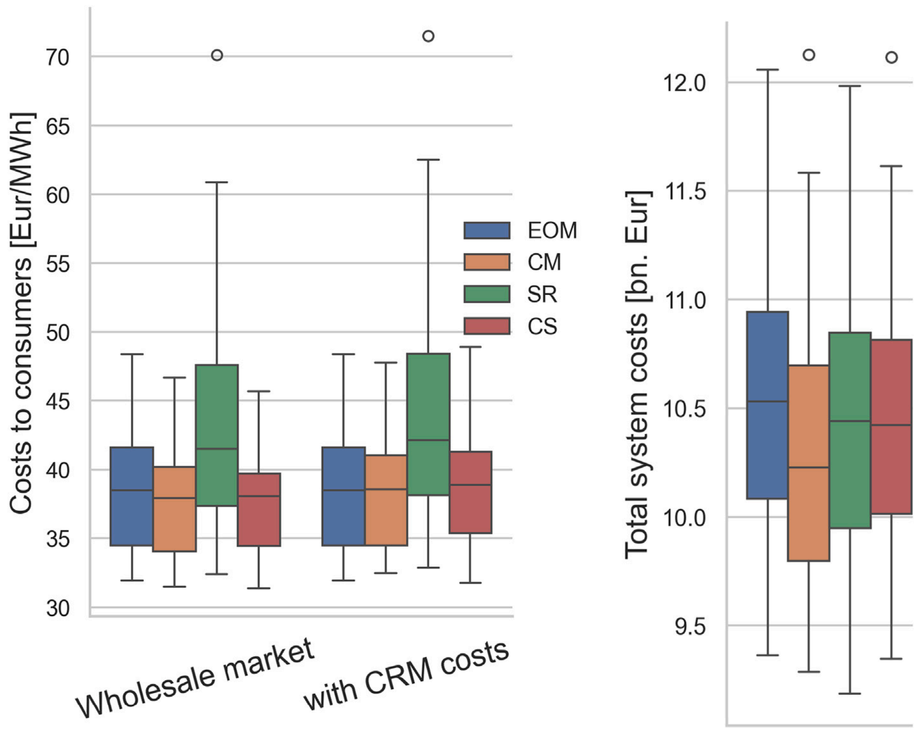


Fig. 21. A CM was the mechanism that reduced total system costs without increasing the costs to consumers.

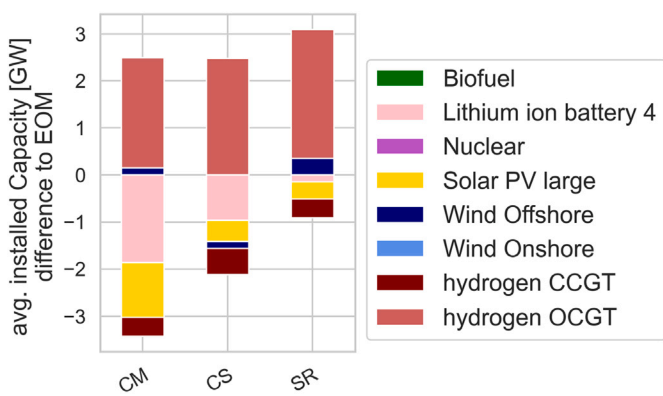


Fig. 22. Difference in the average installed capacity over the last 10 simulation years between CRM scenarios and an EOM.

Similarly, estimating the availability of batteries during shortages is becoming more challenging. Their charging and dispatch strategy has a large influence on the shape of the remaining shortfall and, therefore, on adequacy indicators such as LOLE [32]. Furthermore, battery operators may be exposed to high penalties if these are not available at scarcity moments [64]. Billimoria et al. suggest an alternative way to remunerate batteries through a revenue collar with a soft cap and a yardstick contract basis [65]. An overview of other options can be found in [66].

In our simulations, we don't model long-term contracts; therefore, we observed volatile CM prices, which could bring uncertainty to generators who invest and expect higher compensation but do not receive it consistently each year. This reflects the importance of awarding long-term contracts in CMs.[18] Securing long-term capacity contracts could offer lower capital costs because the debt share could be higher and the equity

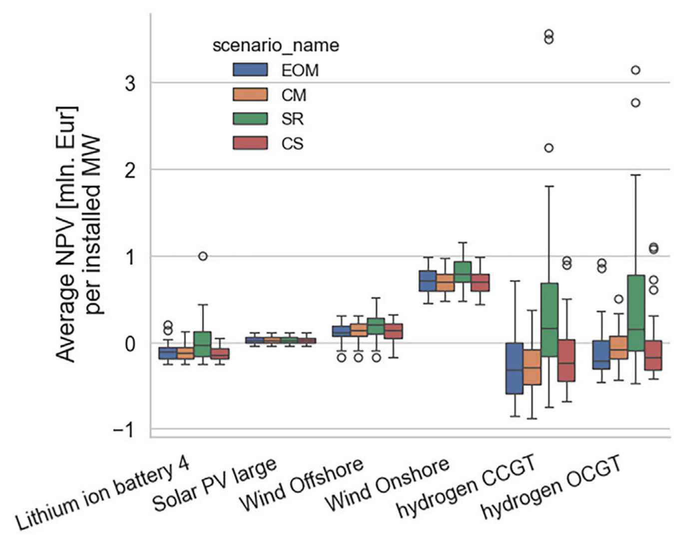


Fig. 23. Normalized annual NPV by technology

returns could be lower [67–69]. An advantage of subsidizing capacity through auctions is the facilitation of a more coordinated deployment while creating competition.

6.2. Strategic reserve

Similar to a CM, setting the SR parameters – mainly the volume and activation price – is becoming more complex. The SR volume and the activation price should be set in such a way that generators outside the reserve do not experience reduced revenues (due to lower scarcity prices compared to the situation without the SR, as the activation price functions as a price cap) [70]. Demand flexibility and

[18] In reality, the majority of capacity market payments are awarded in long-term contracts [2].

storage may set the electricity price during scarcity moments.[19] In these hours, the electricity price will exceed the marginal cost of the most expensive dispatchable unit without a need for activating the reserve. This may complicate the estimation of the net effect of the SR on generator income. Although an SR only pays the generators in the reserve, this mechanism can incentivize more investments by increasing the frequency of scarcity prices. The occurrence of scarcity prices can also increase due to weather uncertainty. However, scarcity prices are not well accepted by consumers, politicians, or network operators [71]. Moreover, when taking into account risk aversion, scarcity pricing methods are not as efficient as promoting the creation of extra capacity through a CM [8]. An alternative mechanism that intends to trigger scarcity prices as a function of how close the system is to scarcity is the operating reserve demand curve (ORDC). Bajo-Buenestado analyzed a system with an ORDC and increasing wind energy and concluded that relying on price scarcity mechanisms might become less effective because the price adder would become more dependent on random weather events [72]. For these reasons, an SR may be used temporarily, when rapid changes in the system are foreseen. During the energy transition, while the flexibility levels and capacity of electrolyzers are low, an SR could prove advantageous, as identified by Holmberg [73]. Nevertheless, in the long term, this mechanism might not be the most suitable.

6.3. Capacity subscription

In the current CRMs, a central authority is responsible for setting the reliability standard and, hence, the demand for capacity. The costs of a CRM are typically socialized as network tariffs. A major advantage of CS is that it does not require a central authority to establish a capacity target. Consumers choose the level of capacity to which they subscribe, providing an accurate signal of the level of demand. Capacity subscription allocates the costs of dispatchable capacity to consumers, making reliability a private good. With CS, consumers are encouraged to be responsive and reduce demand during periods of shortage or invest in private backup facilities (like batteries) if this is cheaper than contracting capacity. Exposing consumers, large and small, to the cost of backup dispatchable capacity provides them with an efficient economic signal, facilitating the needed flexibility in future decarbonized power systems.

However, consumers may find it challenging to determine their need for capacity. Their VOLL is affected by the timing and duration of shortages, as well as whether they were pre-notified. If consumers base their subscription levels on their recent experience with shortages, as was the case in our simulations, they may ignore the risk of extreme weather events. This could lead to demand cycles and volatile prices in the CS market, as we illustrated in our case study. In real life, the ability of consumers to estimate their need for contracted capacity is a key issue in the design of CS. Pilot programs are needed to find out the degree to which consumers can do this. Regulation enforcing a minimum capacity volume, potentially based on the previous year's consumption pattern, may be needed. Furthermore, investors might not solely rely on a three-year average for their investment decisions. Nevertheless, our simulations exemplify that with CS, there is a risk of under- or over-contracting capacity if consumers and generators over-react.

In our simulations, the maximum load limited during scarcity hours was consistently lower than the volume of demand not covered by subscriptions. This indicates that the unsubscribed load was never fully curtailed during periods of scarcity. However, if some consumers wish to consume more than their subscribed capacity, a secondary capacity market could be established wherein unused capacity may be temporarily traded during a scarcity period. We did not simulate this option.

Table 8
Qualitative comparison of CRMs.

	EOM	CM	SR	CS
Limiting shortages	− −	+ + +	+ +[a]	+ +
Reducing total system costs	0	+ +	+	+
Reducing costs to consumers	0	−[b]	− −	−[b]
Reducing electricity price volatility	0	+ +	− − −	+
Incentivizing demand response	+	−[d]	+ +[d]	+ + +
Revenue certainty for investors	− −	+ +[c]	−	+
Avoidance of under/oversizing	+	−	−	+

[a] Involuntary shedding was reduced, but voluntary DSR increased.
[b] Lower costs to consumers if a clawback is implemented.
[c] Higher certainty if payments are awarded in long-term contracts.
[d] Higher if DSR can participate.

An issue with CS is that consumer contract capacity per year. Consumers, especially households and small businesses may be unwilling or unable to sign capacity contracts for more than one year. Consumers may be reluctant to hedge against high energy prices if these prices are not seen often. Secondly, they may encounter difficulties in selecting the consumption level to hedge well in advance. If generation companies cannot secure contracts longer than one year, they may not be able to finance sufficient investment, so the mechanism would not achieve its primary objective. A possible solution could entail a central authority taking the volume risk, acting as an intermediary, buying long-term contracts, and selling them as annual contracts to consumers. This may be a necessary step during the energy transition, while the central purchasing authority might be phased out once the power sector has been decarbonized. If the authority only purchases contracts for low (or zero) carbon dispatchable capacity, the volume risk would be lower during the period that this capacity was phased in. The German government acknowledged this by proposing the integration of a long-term capacity market with a decentralized capacity market into a combined capacity market [74].

In CS, there could also be multiple reliability levels, similar to priority pricing, where consumers receive differentiated electricity prices for different "reliability levels" of consumption [34]. Nevertheless, that would require aggregators to create tariffs based on the number of consumers at each level, making it more flexible but also more complex and less transparent. CS may increase transaction costs, and consumers need a way to handle the complexity. Therefore, we expect that retailers will need to provide simple and transparent offers, guide consumers, and inform them about scarcity in advance. Making reliability a private good can cause equity issues. Low-income households might undersubscribe, and consumers with lower subscription levels could be curtailed disproportionately often. In our simulations, we observed very high CS prices, but these are unlikely because consumers will not be willing to pay more than the cost of a private battery. Energy poverty could be addressed by subsidizing a minimum volume of capacity, although establishing this level of essential demand will be a challenge [27].

7. Limitations of the model and future work

We model the Netherlands as an island system and as a copper plate. Therefore, we do not consider the participation of foreign power plants in the capacity market. We do not simulate market power,[20] risk aversion, or penalties that may be imposed if generators receiving capacity payments are unavailable at a scarcity moment.

We assume that other sectors will trigger hydrogen demand; hence, we did not consider the costs of electrolyzers, hydrogen transport, or hydrogen storage. We also do not consider fuel prices, electricity

[19] Note that we simulated a single DSR activation price. In reality, DSR will be activated at various price levels, resulting in more and smoother scarcity prices.

[20] Suppliers that own pivotal facilities may retire units that could participate in a CM to increase the price, pivotal firms may inflate their bids, or companies may coordinate to extract high prices. [75].

Table 9
Technologies costs [56].

	Investment costs	Fixed costs	Variable costs	Efficiency	Charging efficiency	Discharging efficiency	Energy to Power Ratio	Technical lifetime	Technical limit	COMPETES capacity
	€/MW	€/MW	€/MWh	%	%	%		y	MW	GW
Biofuel	2,400,000	61,676	1.83	31	–	–	–	25	12,040	6.0
Hydrogen OCGT	435,983	7893	4.79	43	–	–	–	25	–	8.4
Hydrogen CCGT	850,698	27,647	4.24	60	–	–	–	25	–	0
Lithium ion battery	220,000	570	1.80	–	92	92	2	25	–	26.1
Lithium ion battery 4	380,000	570	1.80	–	92	92	4	25	–	0.0
Nuclear	7,940,450	111,166	3.50	35	–	–	–	40	–	6.0
Solar PV large	290,000	7400	0.50	–	–	–	–	25	82,099	107.9
Solar PV rooftop	640,000	8900	0.50	–	–	–	–	25	26,964	0.0
Wind offshore	1,640,000	33,000	3.25	–	–	–	–	30	70,000	56.6
Wind onshore	1,090,288	12,059	1.3	–	–	–	–	30	12,000	12.0

Table 10
Other technologies data.

	Max. lifetime extension	Permit time	Lead time	Investment block	Debt interest rate
	y	y	y	MW	%
Biofuel	6	1	3	300	5
Hydrogen OCGT	6	2	2	400	8
Hydrogen CCGT	6	2	2	400	8
Lithium ion battery	1	0	1	300	5
Lithium ion battery 4	1	0	1	300	5
Nuclear	10	2	5	500	8
Solar PV large	3	1	1	300	5
Solar PV rooftop	3	1	1	300	5
Wind offshore	5	1	2	500	5
Wind onshore	4	1	2	500	5

Table 11
Fuel costs [56].

	Eur/MWh
Nuclear	1.69
Biofuel	50.29
Hydrogen	45.07
CO_2	168.00

demand growth, disruptive technology innovations, and other uncertainties. However, a unique uncertainty was sufficient to conceptually illustrate the difference between the effectiveness of CRMs. We assume a well-established hydrogen market with a stable price. In practice, H_2 production will be correlated with VRE production, which may lead to high H_2 prices during weeks with low VRE. With electricity being produced from H_2 during shortage periods, electricity prices may exhibit even greater volatility.

We model national CRMs, in line with most CRMs in Europe. However, capacity markets can cause locational distortions where distant sites are overrewarded if all plants of a single technology are assigned the same DF [62]. Some alternatives are to distinguish DFs by location, to clear CMs ex-ante per zone (as done in Italy), to add locational constraints (as done in Ireland), and to give preference in the market to generators in a location. This and other alternatives could have consequences, for example, on CM liquidity, and should be further investigated.

Furthermore, we recommend simulating the interaction with network tariffs. CS for capacity could also be combined with network tariffs that are based on the same principle of capacity subscription [76], in which case the maximal subscription should be the same for both. In a congested area, consumers could be restricted to a maximal capacity subscription per household.

A possible extension of the model can be to simulate the option for mothballing and de-mothballing. Furthermore, other technologies, such as CCS and long-term storage, could be tested. Moreover, we recommend simulating long-term capacity or energy contracts and exploring possible interactions with a yearly capacity market and capacity subscription. Finally, we recommend researching consumers' preferences between hedging their energy and limiting their load during scarcity moments.

8. Conclusions

We studied the performance of a capacity market (CM), a strategic reserve (SR), and a not-yet-implemented capacity subscription (CS) in a climate-neutral, high VREs system, subject to weather uncertainty. To this end, we developed a co-simulation framework consisting of two agent-based models, AMIRIS, mimicking day-ahead energy market outcomes, and EMLaby, mimicking myopic investment behavior with no equilibrium.

With CM and CS, total costs to consumers remained at similar levels as in an EOM while reducing shortfalls in volume and duration, thus reducing the total system costs. CM and CS offer a choice of whether to remunerate all or only dispatchable generation technologies. The latter appears to be the better choice, because imperfectly estimated derating factors of VREs and batteries can distort the market, and these technologies might not deliver their expected reliability.

With an SR, H_2 turbines that would be decommissioned are kept out of the market; in this way, SR extended the lifetime of these technologies more than the other CRMs. An SR caused volatile and high day-ahead/short-term electricity prices, mainly due to the dispatch of the reserve at the market price cap. The increased price volatility incentivized more investments in H_2 turbines, keeping the capacity of batteries at a similar level to an EOM. However, the price volatility might not be desirable, as the total cost to consumers increases. For this reason, its usefulness appears to be limited to cases in which unprofitable plants need to be kept available for a period, e.g., during the energy transition, until replacements have been built.

In contrast, both a CM and a CS can enhance the security of supply and stabilize electricity bills for consumers. In a CM, a central entity determines the capacity demand curve. Even if only dispatchable technologies can participate in a CM, the derating factors of all technologies have to be established to determine the target capacity. In contrast, with a CS, consumers purchase yearly subscriptions that ensure their electricity supply will not be limited below the subscribed level during periods of scarcity. In our model of CS, consumers base their willingness to pay on experienced shortages, and generators base their investments on CS prices. Because the CS contract duration was one year and due to the assumed limited “memory” of consumers and generators, periodic scarcity events caused investment cycles. We observed larger investment cycles when consumers and generators do not have any “memory” regarding past shortages, ignoring the risk of extreme weather events. Longer-term contracts for capacity could reduce investment cycles, but households cannot be required to sign multi-year electricity contracts. During the energy transition, a solution may, therefore, be that an intermediary agent (a government agency or a regulated entity on behalf of the government) would contract capacity long-term from generators and sell it in annual contracts to consumers. The advantage over a capacity market remains the incentive for consumers to develop flexible solutions behind the meter and the fact that the net demand for dispatchable capacity is revealed.

CRediT authorship contribution statement

I. Sanchez Jimenez: Writing – review & editing, writing – original draft, visualization, validation, software, methodology, investigation, data curation, and conceptualization. **K. Bruninx:** Writing – review & editing, supervision, methodology, investigation, and conceptualization. **L.J. de Vries:** Writing – review & editing, supervision, project administration, methodology, funding acquisition, and conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly and Quillbot in order to improve the grammar. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

Data will be made available on request.

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