CAPACITY REMUNERATION MECHANISMS FOR DECARBONIZED POWER SYSTEMS

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Para mis padres, Alejandra y Jesús.
Gracias por su amor infinito y apoyo incondicional

SUMMARY

In a future power system powered mainly by variable renewable energy (VRE), ensuring a reliable electricity supply during periods of low solar and wind output will be a central challenge. As the revenues of dispatchable technologies are expected to become increasingly volatile, investors may not be willing to invest in sufficient capacity to ensure resource adequacy in all circumstances, including rare scarcity events. To ensure sufficient generation capacity to meet demand at all times, capacity remuneration mechanisms (CRMs) have been increasingly implemented in Europe. This dissertation investigates whether a CRM will be needed and, if so, which mechanism will be most suitable for a decarbonized power system and a power system in transition based in the Netherlands.

This research was conducted within the scope of the Horizon 2020 TradeRES Project - (grant agreement No 864276). [1] The objective of this project was to test innovative electricity market designs that meet society's needs with a (near) 100% renewable power system. Such market designs should provide efficient incentives for both system operation and long-term investment, with this research focusing primarily on the latter. The project was designed to employ agent-based modeling, as this approach enables the simulation of imperfect markets in which actors operate without perfect information, foresight, or coordination. Agent-based models are particularly well-suited to capture long-term dynamics, allowing agents to adapt their strategies over time in response to evolving market conditions.

To evaluate CRMs, we first analyzed current resource adequacy indicators in a study presented in Appendix A. In the future, the intermittence of renewable energy will necessitate increased flexibility. In times of scarcity, storage and flexible demand will increasingly set the price. Given their contribution to balancing supply and demand, it is therefore more appropriate to refer to *system* adequacy rather than solely *generation* adequacy. In a system with substantially more consumer flexibility, scarcity of energy supply may not result in an energy shortage but rather extremely high and unstable electricity prices. During such periods, windfall profits may occur when power prices are significantly greater than the cost of generation. Current adequacy indicators, which are based on outage rates, can be complemented with market signals such as market-based cost recovery and electricity price volatility. These indicators were used throughout this research to compare different market designs.

In Chapter 2, we present the methodology that was applied in the rest of the research. We applied a co-simulation between two agent-based models: AMIRIS and EMLabpy. This research introduces the model EMLabpy, an agent-based model designed to represent myopic investments without assuming a central planner. We applied the co-simulation to a fully decarbonized electricity system dominated by weather-dependent renewable energy based in the Netherlands. We simulated a high level of flexibility from electrolyzers, as well as industrial heating and demand-side response. Furthermore, we simulated a weather-driven heat pump demand and simulated forty weather years. Under these conditions, most of the time, the price was set not by the marginal cost of generators but by the demand's willingness to pay, particularly the electrolyzers' demand. Most scarcity situations and high electricity prices were observed in winter, characterized by low VREs production and high demand from heat pumps. The interannual variability of cost recovery increased by more than threefold, and the annual variability of weighted-average electricity prices increased by more than tenfold, compared with a scenario without weather uncertainty. We demonstrated that if investors based their investments on a year with low VRE, they would not recover their costs. For this reason, in an energy-only market, investors may lack adequate incentives to maintain reliability across all weather years, and CRMs will be needed to ensure resource adequacy.

In Chapter 3, we applied the co-simulation to a similar decarbonized power system to compare the most common CRMs implemented in Europe, a capacity market (CM) and a strategic reserve (SR), as well as a not-yet-implemented CRM, capacity subscription (CS). We simulated weather uncertainty similarly to the previous study, running the model with forty different weather years. In our simulations, a centralized capacity market was the most cost-efficient; this mechanism requires careful parameter setting to avoid under- or overcapacity. 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 may not deliver their expected reliability; moreover, there are other policy instruments to support them.

In CS, consumers purchase yearly subscriptions that ensure their electricity supply will not be limited below the subscribed level during periods of scarcity. CS can incentivize demand flexibility and reveal the actual demand for capacity. However, as the contracts are made with end consumers, their duration is limited to one year. As a result, CS carries a risk that consumers underestimate extreme weather events, undersubscribe, and cause demand fluctuations and volatile CS prices. Moreover, investors might not be sufficiently de-risked with yearly contracts. For this reason, for a decarbonized power system with high flexibility, we recommend implementing a combination of a long-term CM and a CS. In this way, a central authority takes the volume risk in the long-term CM and subsequently sells the credits in a CS, thereby promoting consumers' flexibility.

Finally, we simulated an SR, which aims to prolong the lifetime of the plants in the reserve, thereby increasing the volume of backup capacity. An advantage is that it can be quickly implemented. However, it may cause DSR to be activated more frequently than the plants in the reserve, resulting in higher prices and higher volatility. For these reasons, it is not the most suitable instrument for attracting new investments and improving long-term adequacy.

Finally, in Chapter 4, we applied the co-simulation to a power system in transition. Similar to the last study, we simulated weather stochasticity and analyzed the effectiveness of a CM, an SR, and CS. Since fossil fuel-fueled generators currently receive the majority of capacity payments, in Europe a CO_2 limit has been imposed on the technologies that are eligible for participation in the CRMs. We investigated three scenarios: no limit, a constant limit, and a declining CO_2 limit. With a declining CO_2 limit in a CM, reliability was not compromised, but the total system cost was higher. In a CS, the CO_2 restriction hindered some plants from participating, thereby limiting the positive effects of the mechanism on reliability. An SR was the most effective mechanism for ensuring capacity during the initial simulation years, when renewable energy generation was low. This demonstrates the benefit of an SR, which can be implemented quickly to preserve existing generation plants. This, however, was partly due to the applied weather year sequence. On the other hand, as in the aforementioned study, SR caused the highest price volatility, which is undesirable for consumers and for attracting sufficient long-term investment. For this reason, this mechanism is recommended only in case of a risk of essential power plants being decommissioned, as a provisional measure.

Samenvatting

In een toekomstig energiesysteem dat voornamelijk wordt gevoed door variabele hernieuwbare energie (VRE), zullen de inkomsten van regelbare technologieën naar verwachting steeds volatieler worden. Investeerders zijn mogelijk niet bereid te investeren om in alle mogelijke omstandigheden, inclusief zeldzame schaarste-situaties die voortkomen uit langdurige perioden zonder zonne- en windenergie, te zorgen voor voldoende middelen. Om ervoor te zorgen dat er te allen tijde voldoende opwekkingscapaciteit is om aan de vraag te voldoen, worden in Europa steeds vaker capaciteitsmechanismen (CRMs, *capacity remuneration mechanisms*) ingevoerd. Deze dissertatie beschrijft onderzoek naar de behoefte aan een CRM nodig zal zijn en de geschiktheid van verschillende mechanismen voor een gedecarboniseerd energiesysteem en en tijdens de transitie daarnaartoe in Nederland.

Dit onderzoek is uitgevoerd binnen het kader van het Horizon 2020 TradeRES-project (grant agreement nr. 864276). [1] Het doel van dit project was het testen van innovatieve elektriciteitsmarktontwerpen die voldoen aan de behoeften van de samenleving met een (bijna) 100% hernieuwbaar energiesysteem. Dergelijke marktontwerpen moeten efficiënte prikkels bieden voor zowel operationele beslissingen als voor langetermijninvesteringen; dit onderzoek richt zich voornamelijk op het laatste. Het project is opgezet omvatte het gebruik van agent-based modellen omdat deze aanpak het mogelijk maakt imperfecte markten te simuleren waarin actoren opereren zonder perfecte informatie, vooruitziendheid of coördinatie. Agent-based modellen zijn bijzonder geschikt om langetermijndynamiek te vangen, doordat agenten hun strategieën in de tijd kunnen aanpassen aan veranderende marktomstandigheden.

Om CRMs te evalueren, analyseerden we eerst de huidige indicatoren voor leveringszekerheid in een studie gepresenteerd in Appendix A. In de toekomst zal de intermitterendheid van hernieuwbare energie meer flexibiliteit vereisen. In tijden van schaarste zullen opslag en flexibele vraag steeds vaker de prijs bepalen. Omdat zij bijdragen aan de energiebalans, is het passender om te spreken van voorzieningszekerheid van het systeem in plaats van alleen opwekking. In een situatie met aanzienlijk meer flexibiliteit aan de consumentenzijde is het mogelijk dat schaarste van het energieaanbod niet leidt tot een energietekort, maar wel tot extreem hoge en instabiele elektriciteitsprijzen. Overwinsten kunnen optreden wanneer elektriciteitsprijzen langduring aanzienlijk hoger zijn dan de productiekosten. Huidige indicatoren van voorzieningszekerheid, die gebaseerd zijn op uitvalpercentages, moeten daarom worden aangevuld met marktsignalen zoals marktopbrengsten in verhouding tot kosten en de volatiliteit van elektriciteitsprijzen. Deze indicatoren zijn in dit onderzoek gebruikt om verschillende marktontwerpen te vergelijken.

In hoofdstuk 2 presenteren we de methodologie die in de rest van het onderzoek wordt gebruikt. We hebben een co-simulatie van twee agent-based modellen ontwikkeld, AMIRIS en EMLabpy. Dit hoofdstuk introduceert het model EMLabpy, een agent-based model dat myopische investeringen representeert zonder centrale planning te veronderstellen. We pasten de co-simulatie toe op een volledig gedecarboniseerd elektriciteitssysteem, gedomineerd door weersafhankelijke hernieuwbare energie in Nederland. We simuleerden een hoog flexibiliteitsniveau van elektrolyzers, evenals industriële verwarming en vraagrespons. Daarnaast simuleerden we een weersafhankelijke warmtepompvraag en veertig weerjaren. Onder deze omstandigheden werd de prijs meestal niet bepaald door de marginale kosten van producenten, maar door de betalingsbereidheid van de vraag, met name die van elektrolyzers. De meeste schaarstesituaties en hoge elektriciteitsprijzen traden op in de winter, gekenmerkt door een lage productie van duurzame energie en een hoge vraag van warmtepompen. De interjaarlijkse variabiliteit van de kostenterugwinning nam met meer dan een factor drie toe, en de jaarlijkse variabiliteit van de gewogen gemiddelde elektriciteitsprijzen nam met meer dan een factor tien toe, vergeleken met een scenario zonder weersonzekerheid. We toonden aan dat als investeerders hun investeringen zouden baseren op een jaar met lage VRE-productie, zij hun kosten niet zouden terugverdienen. Om deze reden is het mogelijk dat investeerders in een energy-only markt onvoldoende prikkels hebben om betrouwbaarheid in alle weerjaren te waarborgen, en zijn CRMs nodig om leveringszekerheid te garanderen.

In hoofdstuk 3 pasten we de co-simulatie toe op een vergelijkbaar gedecarboniseerd energiesysteem om de meest voorkomende CRMs in Europa te vergelijken: een capaciteitsmarkt (CM) en een strategische reserve (SR), evenals een nog niet geïmplementeerd CRM, capaciteitsabonnementen (CS, *capacity subscription*). We simuleerden weeronzekerheid op dezelfde manier als in de vorige studie, met veertig verschillende weerjaren. In onze simulaties was een gecentraliseerde capaciteitsmarkt het meest kostenefficiënt; dit mechanisme vereist echter een zorgvuldige parameterinstelling om onder- of overcapaciteit te vermijden. CM en CS bieden de keuze om alle of alleen regelbare opwekkingstechnologieën te vergoeden. De laatste optie lijkt beter, omdat onjuist geschatte deratingfactoren van VRE en batterijen de markt kunnen verstoren en deze technologieën mogelijk niet de verwachte betrouwbaarheid leveren; bovendien bestaan er andere ondersteuningsinstrumenten voor deze technologieën.

In CS kopen consumenten jaarlijkse abonnementen die garanderen dat hun elektriciteitslevering tijdens schaarste niet onder het geabonneerde niveau wordt beperkt. CS kan vraagflexibiliteit stimuleren en de werkelijke vraag naar capaciteit zichtbaar maken. Omdat de contracten met eindgebruikers worden afgesloten, is de looptijd echter beperkt tot één jaar. Hierdoor bestaat het risico dat consumenten de kans op extreme weersomstandigheden onderschatten, te weinig capaciteit afnemen en schommelingen in de vraag en volatiele CS-prijzen veroorzaken. Bovendien bieden jaarcontracten mogelijk niet voldoende risicodekking voor investeerders. Daarom bevelen wij voor een gedecarboniseerd energiesysteem met hoge flexibiliteit een combinatie van een langetermijn-CM en een CS aan. In deze optie neemt een centrale autoriteit het volumerisico op zich in de langetermijn-CM en verkoopt vervolgens de capaciteitscontracten door in de vorm van een CS, wat flexibiliteit aan de vraagzijde bevordert.

Ten slotte simuleerden we een SR, die tot doel heeft de levensduur van installaties in de reserve te verlengen en zo het volume van back-upcapaciteit te vergroten. Een voordeel is dat deze snel kan worden geïmplementeerd. Een SR kan echter ertoe leiden dat vraagreductie (DSR) vaker wordt geactiveerd dan de installaties in de reserve, wat resulteert in hogere prijzen en meer volatiliteit. Om deze redenen is dit niet het meest geschikte instrument om nieuwe investeringen aan te trekken en de voorzieningszekerheid op lange termijn te verbeteren.

Tot slot pasten we in hoofdstuk 4 de co-simulatie toe op een energiesysteem in transitie. Net als in de vorige studie simuleerden we weerstochastiek en analyseerden we de effectiviteit van een CM, een SR en CS. Aangezien fossiel gestookte generatoren momenteel het grootste deel van de capaciteitsbetalingen ontvangen, is in Europa een CO_2-limiet opgelegd aan technologieën die in aanmerking komen voor deelname aan CRMs. We onderzochten drie scenario's: geen limiet, een constante limiet en een dalende CO_2-limiet. Met een dalende CO_2-limiet in een CM werd de betrouwbaarheid niet aangetast, maar de totale systeemkosten waren hoger. In een markt met CS beperkte de CO_2-restrictie de deelname van sommige installaties, waardoor de positieve effecten van het mechanisme op de leveringszekerheid werden verminderd. Een SR was het meest effectief om capaciteit te garanderen in de eerste simulatiejaren, toen de productie van hernieuwbare energie laag was. Dit toont het voordeel van een SR, die snel kan worden geïmplementeerd om bestaande centrales te behouden. Dit was echter deels te wijten aan de gebruikte reeks weerjaren. Anderzijds veroorzaakte SR, net als in de eerdergenoemde studie, de hoogste prijsvolatiliteit, wat onwenselijk is voor consumenten en voor het aantrekken van voldoende langetermijninvesteringen. Om deze reden wordt dit mechanisme alleen aanbevolen wanneer er risico bestaat dat essentiële elektriciteitscentrales worden ontmanteld, als tijdelijke maatregel.

CONTENTS

LIST OF ABBREVIATIONS

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
CPP	Critical Peak Pricing
CRM	Capacity Remuneration Mechanism
CFD	Contract for Difference
CS	Capacity Subscription
DSR	Demand Side Response
DER	Distributed Energy Resources
EMLabpy	Energy Modelling Laboratory Python
EOM	Energy-only-Market
$ENTSO-E$	European Network of Transmission System Operators for Electricity
EV	Electric Vehicle
FLH	Full load hours
GA	Global ambition
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
TSO	Transmission System Operator
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_2T	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

1

INTRODUCTION

1.1. MOTIVATION

The European Union aims to be climate-neutral by 2050 [2]. By 2050, the share of electricity produced by renewables is projected to reach more than 80%. In September 2020, the European Union increased the target to reduce greenhouse gas emissions by 2030, compared to 1990, to 55% [3]. We refer to this shift from fossil-fuels as the energy transition. A decarbonized society will require electrifying many sectors of the economy, including transportation and heating. This will increase the uncertainty regarding both demand and flexibility levels. Moreover, considerable uncertainty will emerge from the deployment rate of transmission networks, weather uncertainty, among other factors. Year-on-year variations pose a significant challenge for dispatchable technologies, which will be activated for a limited number of hours and may not be able to recover their investment costs in the wholesale market.

One of the greatest challenges of a near 100% VRE-based power system will be to secure the supply of electricity during times of scarce solar and wind energy, also known as dark doldrums or Dunkelflaute. This is becoming increasingly relevant as the share of electricity from these sources, as well as the frequency of extreme weather events are increasing. This thesis focuses on investigating the effect of weather uncertainty on resource adequacy. We focus our research in the Netherlands, where the electricity system's reliability is expected to decline beyond 2028 and to surpass the Dutch norm of 4 hours per year of loss of load expectation (LOLE) to a LOLE of 14.2 by 2033. TenneT considers the main reasons for this adequacy challenge to be the Prohibition of Coal in Electricity Production Act, which mandates a phase-out of coal-fired generation by 2030, the potential closure of unprofitable power plants, and the increasing demand for electricity [4]. We add the question of how to provide sufficient controllable power generation capacity in an electricity market with an increasing share of solar and wind energy.

During the transformation of the European energy system, its regulation needs to ensure that the three goals of energy policy are balanced. The energy trilemma refers to the challenge of balancing the objectives of increasing sustainability and guaranteeing reliability while keeping system costs affordable. In addition to building generators to cover the peak residual load, which occurs when demand is high and variable renewable energy production is low, consumers' flexibility can be enhanced to ensure that demand and generation are balanced at all times. Consequently, future market designs should evolve to enable the necessary flexible resources in the system. Resource adequacy traditionally denotes the capacity of the power system to supply enough electricity to meet demand at all times. In this dissertation, we use the term system adequacy, as both generation and demand need to be adaptable. This dissertation investigates a decarbonized power system and a power system in transition under high levels of flexibility. [1]

Underinvestments can be more costly for society than overinvestments. During rolling or complete blackouts, sustained high scarcity prices can cause high money transfers on top of the high outage costs, in contrast to an overinvestment situation, where consumers would benefit from low prices while the costs of additional capacity are relatively modest. [6, 7] The catastrophe in Texas exemplifies this situation. In February 2021, millions of households were left without water and power during an extremely cold winter storm. Although the outage was mainly caused by inadequate infrastructure winterization, which led to a failure of the gas supply, the situation illustrates the risks of insufficient backup capacity and energy storage during prolonged times of extreme weather situations and a lack of wind and sun. [8] Even with demand rationing, the costs to society can be very high. For example, in California in the summer of 2020, the very high use of ACs coincided with insufficient capacity, resulting in rolling blackouts that avoided a system collapse but did not prevent prices of 400 USD/MWh, up from an average of about 30 USD/MWh.[9, 10] The most recent event was seen in the winter of 2024, when many countries experienced very high electricity prices due to a couple of cold doldrums that extended for several days. For example, in Germany on December 12th, 2024, wind energy production was 3.1 GW, which was 85% lower than the average production of 19.2 GW. On top of that, the consumption was relatively high due to cold weather, and this caused high energy prices. [11] This caused peak prices of 936 €/MWh even if the security of supply was never at risk. [12]

To ensure system adequacy, capacity remuneration mechanisms (CRMs) have been introduced in various electricity markets across the world. These are measures that remunerate electricity capacity providers for being available to supply electricity or reduce demand when needed. [2] Between 2020 and 2024, payments related to CRMs more than doubled. Over fifty percent of the generators in Europe are subject to a CRM [13]. In the most recent amendments of the electricity market design regulation [5], CRMs stopped being recommended as temporary measures.

Although CRMs have been researched for a long time, there is no consensus on which mechanism is most suitable for future systems. Cramton [14] describes two objectives for electricity market design. The first one is to make the best of existing resources. The second one is to ensure that markets provide the proper incentives for efficient long-run

[1] The electricity market design reform defines flexibility as "the ability of an electricity system to adjust to the variability of generation and consumption patterns and to grid availability, across relevant market timeframes." [5]

[2] The electricity market design reform defines a CRM as "a measure to ensure the achievement of the necessary level of resource adequacy by remunerating resources for their availability, excluding measures relating to ancillary services or congestion management" [5]

investment. In a high-renewable power system, the key enabler for a cost-efficient market design will be flexibility. A future CRM should enable the participation of resources (generators and consumers) that can help balance the intermittence of VREs. A future power system will no longer be designed to enable sufficient *resources*, but to achieve sufficient *system* adequacy.

However, the question remains: How can system adequacy be maintained in a decarbonized power system? In this dissertation, I explore this question.

1.2. RESEARCH QUESTIONS

The overarching question of this dissertation is:

How can system adequacy be maintained in a decarbonized power system?

To answer this question, the following sub-questions were addressed:

- **In a future power system with almost 100% VREs, can an energy-only-market enable resource adequacy?**
- **What are the strengths and weaknesses of capacity remuneration mechanisms in an almost 100% renewable energy system?**
- **How does the transition from a conventional to a renewable electricity system change the requirements for a capacity mechanism?**

1.3. THESIS OUTLINE

The remaining part of this chapter introduces the fundamentals that are needed for understanding the next chapters. Section 1.4 introduces key concepts of investment theory and provides an overview of the current state of CRM proposals, including the mechanisms examined in this dissertation. Next, section 1.5 reviews energy system models and describes the methodology used in this dissertation. This research was funded and conceptualized as part of the TradeRES consortium, whose objective is summarized in section 1.6.

To compare market designs, we researched current performance indicators for resource adequacy and proposed market signals as complementary indicators, presented in Annex A. In the initial conceptualization of the research, we attempted to co-simulate an optimization model (COMPETES) for the dispatch decisions with an agent-based model (EMLAB) for the investment decisions. This resulted in many challenges, and therefore, the method was not implemented. The lessons of this exercise, presented in Annex B, enabled an easier co-simulation of AMIRIS and EMLab, which was used for the simulations in this research.

All our case studies resemble a power system based on the Netherlands. In chapter 2, we studied a decarbonized power system and analyzed the impact of weather stochasticity on the results of an energy-only-market. In a similar setting, we studied the three most predominantly implemented capacity remuneration mechanisms, presented in chapter 3. Finally, in Chapter 4 we studied the same CRMs but in a case study during the energy transition, considering different CO_2 limits on the eligibility of power plants.

After presenting the findings, the research questions are answered in a concise manner in subsection 5.1. Subsection 5.2 discusses relevant aspects of CRMs that were not simulated and proposes directions for further research. The next subsection, 5.3.1, reflects on the methodology learnings, limitations, and future research proposals.

Finally, the conclusion summarizes the findings, deriving policy advice in chapter 6.

1.4. INVESTMENT THEORY

The theory of spot pricing by Schweppe and Caramanis [15] states that under perfect competition, perfect foresight, and risk neutrality of investors, spot pricing and a price cap equivalent to the average value of lost load (VOLL) can lead to an optimal investment for electricity generation. However, it is not likely that all these requirements are met.

The so-called missing money problem, which makes it difficult to recover investment expenditures, is the result of multiple reasons. To avoid extreme price spikes, regulators in Europe have imposed a maximum clearing price for single day-ahead coupling, which is lower than consumers' Value of Lost Load (VOLL). [3] Following the surge in electricity prices from 2021 to 2023, several EU members introduced price caps to shield consumers from extreme electricity prices. Additionally, out-of-market interventions, such as voltage reduction and rolling emergency load shedding, may hinder the price formation during scarcity. [17] Finally, an increasing share of VRE has depressed prices in times of abundant wind and solar energy. [18] In many European countries, VRE plants receive support per produced energy (MWh) and bid up to the negative value of their subsidy[4], which, combined with inflexible conventional plants, has increased the frequency of negative prices in the wholesale markets.

Even if there are enough price spikes for fossil plants to recoup their investments and cover the fixed costs, investors might not be willing to take the risks. Regulatory uncertainties regarding CO_2 pricing, nuclear development, and coal phase-out contribute to investors' risk aversion. Newbery [19] defined the missing market problem as the situation where generators can potentially receive adequate revenues in the market, yet companies or their financiers do not perceive this. The issue arises when the investors lack hedging options to secure the investment risks associated with future market interventions. This can be partially attributed to random curtailments, wherein hedged consumers face the same likelihood of being curtailed as unhedged consumers. This situation creates a reliability externality, as no retailer incurs the cost of failing to secure energy in advance [20]. One of the main reasons why markets might not be sufficient to ensure security of supply (SoS) [5] is that it constitutes a public good. SoS is non-excludable and non-rivalrous because if the supply is not sufficient, consumers are randomly disconnected, and if there is more capacity, all consumers benefit. Several authors agree that the problem could be partially solved if SoS becomes a private good, as explained in subsection 3.2.2. Furthermore, the missing market can be caused by increased competition at the retail level, which causes wholesale buyers to be hesitant to enter into long-term agreements with generators out of concern about unfavorable changes in electricity prices and their limited ability to pass on the costs of long-term contracts, as rivals can undercut with cheaper spot market prices. [22]

[3] In 2022, the maximum clearing price was increased from 3000 to 4000 Eur/MWh.[16]

[4] However, this is changing in some countries. In Germany, plants under the Renewable Energy Sources Act no longer receive remuneration during net price hours, and in the Netherlands, subsidies are no longer paid if electricity prices are negative for more than six consecutive hours.

[5] SoS is defined as the existence within a system of sufficient generation and transmission capacity to meet the load, whether under normal or unusual conditions, such as unavailability of facilities, unexpected high demand, low availability of renewable resources, etc." [21]

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1.4.1. Capacity Remuneration Mechanisms - Status Quo

Unlike an energy-only market (EOM), in which power generators are paid only for the electricity produced and sold, capacity remuneration mechanisms (CRMs) are policy instruments where electricity producers are paid for being available to generate (or reduce demand) when needed, addressing the issues of missing money and missing markets. The literature about CRMs is extensive, and multiple sources have summarized details about CRMs in European countries and worldwide [23, 24]. The purpose of this subsection is not to give an extensive description of the different CRMs, but to analyze the most relevant recent proposals.

If generating companies are risk-averse, under the uncertainty of investment recoup, CRMs can help reduce risk aversion. Furthermore, CRMs can reduce investment waves, which are partly caused by investors' myopic behavior, long permitting and construction times, etc. [25, 26]. Although more recently, some generators, i.e. batteries and solar PV, can have shorter lead times. The uncertainties about supply and demand levels, fuel, and CO_2 prices remain large, and the risk of investment waves remains large. Nowadays, most investments in VREs are subsidized through auctions, providing a better estimation of the deployment of VREs. However, these projects can be delayed due to construction, materials, and labor bottlenecks, as well as materials costs, social opposition, among others.

Multiple studies have shown that reducing investment risks reduces the cost of capital [27]. For VREs and technologies with near-zero marginal costs, this can be achieved through contracts for differences (CfD). For dispatchable technologies with high marginal costs, CRMs can act as insurance where generators receive a constant payment instead of relying on rare scarcity prices. This is valid if CRMs are awarded long-term contracts. On the negative side, one of the most relevant criticisms of CRMs is that they can slow down the transition. Mays et al. showed that CRMs favor resources with lower fixed costs and higher operating costs, which makes them suboptimal for low-carbon systems [28]. More advantages and disadvantages of each mechanism will be analyzed in the next subsections.

CRMs are usually divided into two categories: price-based and volume-based, depending on how compensation is given. Price-based mechanisms are, for example, capacity payments, in which generators receive a fixed payment per MW installed. These payments result in a capacity level and can easily result in under- or over-investment. In a quantity-based mechanism, an authority sets the desired level of installed capacity, and through auctions, the market clears at a price. This applies to the capacity market and strategic reserve. [24] In this dissertation, CRMs are categorized based on the way they favour flexibility and based on their payment mechanism.

In Figure 1.1, on the x-axis CRMs are sorted on the degree to which they favor flexibility, including demand-side-response (DSR) [6] which will be key enablers of a decarbonized power system. Enabling the flexibility of consumers could be the most cost-effective way to ensure resource adequacy.

[6] The regulation 944 [29] defines in Art 2.20 demand response as the "change of electricity load by final customers from their normal or current consumption patterns in response to market signals, including in response to time-variable electricity prices or incentive payments, or in response to the acceptance of the final customer's bid to sell demand reduction or increase at a price in an organized market... whether alone or through aggregation "

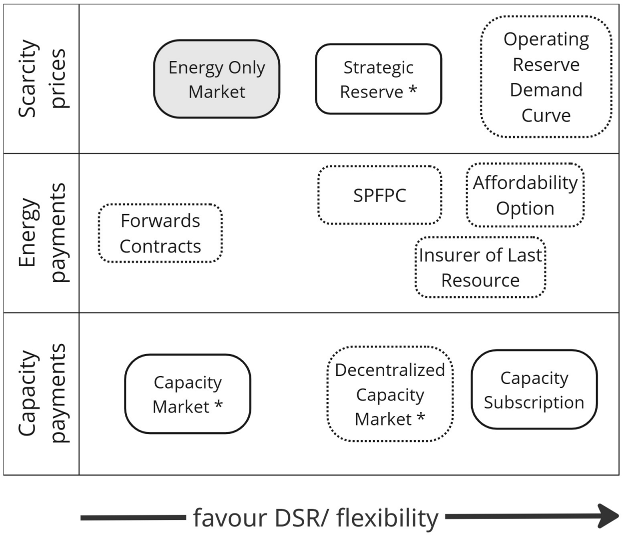

Figure 1.1: Categorization of CRMs. On the x-axis, CRMs are classified based on their compatibility with flexibility, and on the y-axis based on the mechanism to promote adequacy. The CRMs marked with * can also be designed to award DSR and potentially favour more flexibility. The CRMs delineated by a solid line were modeled in this dissertation, including an EOM, which is not classified as a CRM.

On the y-axis, CRMs are categorized based on their mechanism to promote adequacy via short-term scarcity prices, energy remuneration, or capacity remuneration. This is not an exhaustive list; there are other categories of mechanisms, such as obligations for flexibility. 1.4.1.

In this study, we contrast two CRMs that incentivize capacity through capacity payments (capacity market and capacity subscription) with one that does it through scarcity pricing, a strategic reserve. The following subsections summarize the most relevant CRMs, categorized by their mechanism to promote adequacy.

INCENTIVIZING CAPACITY THROUGH CAPACITY PAYMENTS

This subsection offers an overview of the CRMs that promote adequacy through capacity payments and that are modeled in this thesis.

CAPACITY MARKETS (CM)

In a centralized CM, a central authority -for example, the national transmission system operator (TSO)- is responsible for estimating the volume of capacity that is needed to ensure a reliability level that is optimal. As shown in Figure 1.2, both a deficit and an excess of capacity increase the system costs. In case of a capacity deficit, involuntary load shedding costs increase. These costs can be calculated by multiplying the Energy Not Served (ENS) by the Value of Lost Load (VOLL), which is the consumer's maximum willingness to pay. In the case of excess capacity, the involuntary shedding costs decrease, but the costs of capacity and its operating costs increase. The annual capital and fixed

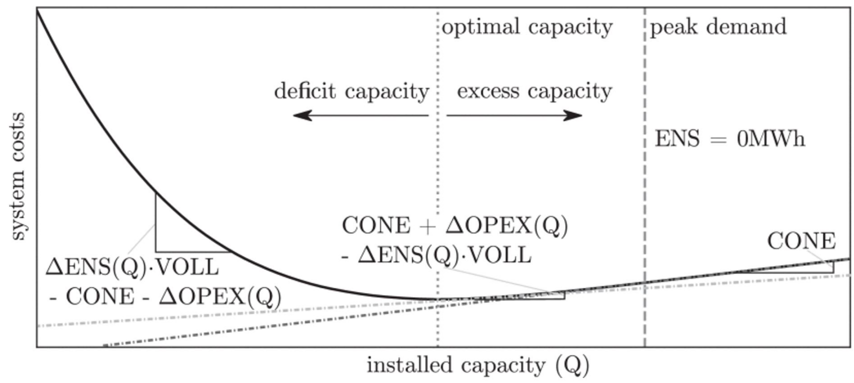

Figure 1.2: System costs as a function of installed capacity, based on [7, 30]

costs for a reference technology are known as the cost of new entry (CONE). In a simplified manner, the optimal adequacy level is calculated as the balance between the CONE of the cheapest reference technology and the VOLL and OPEX as denoted in equation 1.1. [30]

$$LOLR_{RS} = \frac{CONE}{VOLL - OPEX} \tag{1.1}$$

In a centralized capacity market, the demand for capacity is typically set with a sloped demand curve, which enables more stable prices and avoids market power. A detailed description is offered in section 3.3.2. The price of the capacity payment is set by a centralized auction. Capacity providers receive the payments, and the costs are allocated across retailers according to their customers' contribution to peak demand. The central 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 their preferences [31]. In contrast, in a decentralized capacity market, the responsibility for setting the demand is distributed. Retailers must buy capacity certificates that can cover their customers' consumption during peak hours, and these are procured in bilateral trading rather than a central auction.

Several markets in Europe have implemented centralized capacity markets, i.e., the UK, Ireland, Belgium, France, Italy, Poland, and a decentralized capacity market has been implemented in France. Also, some independent system operators (ISO) in the USA have implemented capacity markets, such as PJM, ISO New England, New York ISO, and Midcontinent ISO. The European Electricity Regulation [32] stipulates that CRMs should be technology-neutral, yet Member States should promote non-fossil flexibility such as DSR and storage in CRMs. Wind and solar can also participate in this mechanism, but their capacity is de-rated according to their contribution to reliability. The de-rating can be based on the historical production during peak demand or on probabilistic simulation models [33]. Batteries can also participate in many capacity markets, but their contribution is also de-rated because they can only deliver energy for a limited number of hours. Birkett suggests making two pots, one for established firm low-carbon technologies such as gas-fired plants, short-duration battery storage, hydro pump, and DSR, and a second one for early-stage resources [34].

A disadvantage of CMs is that they can undermine the function of wholesale markets to provide signals for investments and can cause reliance on extra interventions. Newbery [19] explains that capacity auctions tend to be overprocured, which can exacerbate the missing money problem instead of relieving it.

CAPACITY SUBSCRIPTION

An alternative to a capacity market, where a central authority determines the needed level of capacity, is to shift the responsibility for establishing the demand from retailers and TSOs to consumers, making the quality of supply a private good. In recent years, several proposals have emerged to achieve this, as explained in subsection 3.2.2. In a capacity subscription (CS), consumers choose the volume of energy they need during scarcity. In this way, consumers are incentivized to be flexible and manage their energy consumption. During scarcity periods, the TSO limits the energy based on the capacity subscribed level chosen by the user. To avoid complexity, the TSO could curtail the load-limiting devices (LLD) that consumers choose in an automatic way after sending a warning signal some time ahead. Further details about the implementation of this mechanism are described in [35].

RELIABILITY OPTIONS

Reliability options (RO) are financial instruments where capacity providers receive a fixed capacity payment but are obliged to pay back to system operators the difference if electricity prices exceed a strike price. [36, 37] A shortcoming of capacity markets has been the low penalties for being unavailable in times of system stress. In Great Britain, the maximum monthly penalty is equivalent to two monthly capacity market payments, and this non-delivery penalty only enters into force when some consumers are disconnected from the network due to a lack of generation [34]. Introducing reliability options, the penalty is higher, as those plants that commit their capacity receive a penalty at the market price when they are unavailable.

INCENTIVIZING CAPACITY THROUGH SCARCITY PRICES

This subsection offers an overview of the CRMs that promote adequacy through scarcity prices. In this dissertation, only the strategic reserve was modeled.

STRATEGIC RESERVE

A strategic reserve (SR) consists of a group of power plants that are contracted to be kept out of the wholesale market and remain available for scarcity situations. This mechanism is implemented to extend the lifetime of some power plants in case of a foreseen adequacy risk. Typically, the TSO designates a volume of generation capacity to be held in reserve. The TSO activates the plants only in situations of scarcity. The EU regulation specifies that “the strategic reserve resources should be dispatched after the TSO exhausted their balancing resources... during imbalance settlement periods, imbalances in the market are to be settled at least at the VOLL;” [32]. The TSO covers the fixed costs of power plants that have a low probability of being activated in order to avoid mothballing. In case the plants are activated, the TSO keeps the difference between the market revenues and the marginal costs of the plant to offset the cost of the reserve. The European Commission has established in Regulation (EU) 2019/943 Article 21 that the member states should evaluate if an SR is capable of addressing the resource adequacy concerns. If this is not the case, another mechanism may be implemented. [32]

ORDC

Similar to a strategic reserve, an Operating Reserve Demand Curve (ORDC) intends to promote scarcity prices to incentivize new investments and flexibility. However, no power plants are removed from the market, and therefore, there is no need for consumers to pay for a reserve regardless of its activation frequency. An ORDC is designed to raise prices in a smooth manner through a price increase. The market operator prices the value of different reserve levels considering the Loss of Load Probability (LOLP) at each level and the VOLL. For example, in the ORCD in Texas, when the level of reserves is high, then the LOLP falls to zero and the price adder remains at zero. When operating reserves drop below 2 GW, the price is adjusted to the VOLL 9000 \$/MWh. After the blackouts in 2021, the price cap was adjusted to a lower VOLL of 5000 \$/MWh and the minimum contingency level (the reserve at which price reaches VOLL) to 3 GW. [38]

INCENTIVIZING CAPACITY THROUGH ENERGY PRODUCTS

This subsection offers an overview of the CRMs that promote adequacy through energy payments. None of these CRMs were modeled in this dissertation.

Bilimoria et al. [31] propose a mechanism in which consumers with a high VOLL pay for insurance. If insured consumers are curtailed, they are compensated. The insurer-of-last-resort uses the insurance premium to pay for the costs of plants in a strategic reserve. They argue that to alleviate equity issues, the government can offer subsidies to consumers.

Another proposal by Schittekatte and Batlle is Affordability options (AO). AOs are designed to promote long-term contracts while preventing large income transfers during sustained high prices, protecting consumers against high prices. Similar to RO, long-term contracts are made with generators, but instead of entering into force when prices are above a relatively high strike price, in affordability options, the payoffs are activated if the average of all prices over a period exceeds a lower strike price. They argue that what is relevant is to avoid very high monthly bills rather than very high prices for a few hours. Consumers pay a fee for this "insurance".[39]

Wolak [20] proposed another mechanism: Standardized fixed price forward contracts (SFPFC), which require retailers 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. Wolak argues that generators are best positioned to offer reliability contracts and that obligations could be shaped according to the hourly shares of total system demand and allocated to retailers based on their share of system demand during the month. The regulator could increase the share of demand that it purchases to increase reliability. Through SFPFC, generation owners can decide the capacities and the mix of technologies to meet their obligations and seek to minimize the cost of supplying by buying or producing, which makes them bid the true marginal cost in the short-term market. This mechanism also aims to develop a liquid market for bilateral contracts. Contracts should be set up to four years in advance. Shu and Mays [40] simulated this mechanism and observed that intermittent technologies might be risk-averse to offer such forwards. Wolak argues that forcing generators to offer contracts would shift the risk from retailers to generators, which could enhance competition in the wholesale market; however, Shu and Mays argue that this could lead them to incorporate higher risk premium prices [40].

Similarly, Batlle et al. [41] proposed that suppliers should ensure a level of hedging. However, they explain that if customers change providers in large numbers, small suppliers could more easily default as they could not cover their bilateral long-term contracts. Similarly, small generator companies pose a significant counterparty risk for suppliers and retailers.

OBLIGATIONS FOR FLEXIBILITY

Finally, Cremer [42] proposed obligations for flexibility, where retailers would need to keep a percentage of their consumers' demand as flexible. Retailers could develop tailor-made products for their customers, and consumers would choose between the quality of service and the tariff price. Consumers could receive a payment or a price reduction for energy not being delivered. Although this mechanism could be cost-effective, it might not incentivize more capacity because there are no extra payments for generators.

1

1.5. MODELLING METHODS USED IN THIS DISSERTATION

1.5.1. ENERGY SYSTEM MODELING METHODS

There are numerous techniques to model energy systems: optimization models, simulation models, models focused on power systems and electricity market models, and qualitative mixed research models. [43]

In optimization models, the best possible outcome is calculated considering the physical and regulatory constraints. In general, optimization models assume a market equilibrium. These models aim to find the cost-optimal state based on fully rational actors with perfect information about the future power system and a perfect market, with no strategic decisions. Most capacity-expansion optimization models have the objective of finding the state with minimal cost to meet the load. They assume perfect information and central coordination, under which cost recovery of all investments is guaranteed. Similarly, multi-agent systems (MAS) simulations aim to find an equilibrium for a problem using agents.

In contrast, ABM's objective is to explore the emergent properties of systems without the need to reach an equilibrium state. [44] ABMs enable simulating markets that evolve over time and thus allow exploring path dependency and agents with myopic behavior. ABMs allow agents to be programmed with reinforcement learning, rules, or heuristics. In this way, ABMs allow simulating a more realistic scenario in which agents make decisions based on limited information. Furthermore, ABMs are adaptable in terms of their foresight timeframe. On the downside, ABMS can be very sensitive to the chosen heuristics and can become very complex and difficult to interpret.

1.5.2. AGENT-BASED-MODELLING IN ELECTRICITY MARKETS

Agent-Based Modeling (ABM) is the computational modeling of processes as open-ended dynamic systems of interacting agents with defined behavior rules that make the agents interact among themselves and with the environment, leading to emergent system-level behavior. Agents are software entities within a computationally constructed world capable of acting based on their own state, i.e., their own internal data, attributes, and methods. In an ABM, agents are autonomous and modular and repeatedly execute behaviors or decisions based on conditions in a dynamic environment. ABMs have been applied to explore a wide range of phenomena in social, behavioral, cultural, physical, biological, and energy systems domains, as done in this dissertation. [45]

Capacity expansion is a complex decision process. The energy transition involves a long period in which the energy markets are not in equilibrium, as a result of which expectations about the future, emerging state of the system play an important role in investment decisions. ABMs allow the exploration of the dynamics over time of agents that invest in capacity. In capacity-expansion ABMs, the investing agents can be modeled as profit-seeking agents, can be given memory and limited information, and can interact with other agents. The objective of the agents is to maximize the net present value of their portfolio. These models offer the possibility to simulate market imperfections such as investors' risk aversion, market power, bounded rationality, and imperfect information. The latter is a common phenomenon often seen in electricity markets. For example, in the Netherlands, there was an overestimation of the demand, which led to the commissioning of three coal-fired plants in 2015 [46]. Currently, in Germany, triggered by high volatility in electricity markets, there is a rush to build batteries [47] while later investments in flexible generators could worsen the expected revenues. ABMs allow for simulating these types of boom-bust cycle dynamics and to simulate market designs such as capacity markets [48].

Capacity markets have also been modeled using other types of models. Bothwell and Hobbs simulated a capacity market using a single linear-programming optimization, in which installed capacity had to cover peak the demand plus a reserve margin, and the shadow price on the capacity constraint equaled the capacity price [49]. Another method is the mixed complementarity problem, a mathematical programming formulation that allows representing policies by treating market players as independent problems rather than a central optimization [50].

Short-term market optimization models solve the dispatch of a perfectly coordinated market. However, they may not reflect real-world decisions. In contrast, short-term market ABMs follow a bottom-up simulation of individual market participants. AMIRIS, for example, allows simulation of markups and markdowns for conventional power plants, bidding according to renewable support and storage dispatch planning with a rolling time horizon. Torralba et al. quantified the difference between the system costs of fundamental optimization and AMIRIS, an ABM model that simulates dispatch decisions in the wholesale market, and confirmed that the short-sightedness and market power of participants result in the largest deviation from optimal investments, especially in systems with high-RES penetration; an ABM resulted in ca. 4% higher costs [51]. In this research, we simulated investment and dispatch decisions with ABMs as explained in the next subsection 1.5.3.

1.5.3. CO-SIMULATION

This research was funded by the TradeRES consortium, which aimed to combine the strengths of its members' models. We applied a co-simulation of two agent-based models: EMLabPy simulated investment decisions, and AMIRIS simulated dispatch decisions.

EMLabpy was developed in Python and inspired by the Energy Modeling Laboratory (EM-Lab) model developed at TU Delft. [52] The model simulates power companies' investment decisions in generation capacity under conditions of limited information and imperfect investment behavior. Other ABMs have previously been applied to simulate investment decisions in the energy industry. Some are EMIS-AS [53], PowerACE [54], ElecSim [55], among others [56]. Refer to subsection 2.2.3 and EMIS-AS [53] for a comparison of these models.

AMIRIS [57] was developed by the German Aerospace Center (DLR) and simulates business-oriented bidding in the wholesale market. AMIRIS simulates power plant operators, traders, policy agents that provide support instruments, demand agents, and flexible agents that seek to maximize their profits. In AMIRIS, a unique storage agent's dispatch is solved through dynamic programming and is planned on a rolling time window basis. AMIRIS was developed Both models were co-simulated using Spinetoolbox, which is a platform developed by the Technical Research Centre of Finland (VTT).

Rather than augmenting the functionalities of energy models, energy models can be linked with each other to simulate a broader scope. Linking or coupling models entails the exchange of information, where the output of one model functions as the input for another. In soft-linking, a model can complete its full function without a linkage with another model; it allows the user to control the transfer of information, facilitating iterative data exchange. In hard-linking, a model cannot complete its full function without being linked to another model; one model exchanges data with the master model while both run at the same time. [58] Co-simulation is a type of hard-linking where the inputs and outputs are exchanged in a specific time step, and based on the information, the simulation progresses to the next step. Linking models involves utilizing the output of one model as the input for another model without requiring time synchronization, while co-simulation does. A more detailed explanation of the co-simulation applied in this dissertation is presented in Chapter 2.

1.6. CONTEXT OF THE RESEARCH

This research was conducted within the scope of the Horizon 2020 TradeRES Project. [59] The objective of this project was to test innovative electricity market designs that meet society's needs with a (near) 100% renewable power system. The project was conceived in 2018 and began in early 2020. At that time, there was greater confidence in market-driven investments than is now the case in Europe. The energy crises of 2022 and 2023, with their extremely high but short-lived electricity prices, increasing electrification and uncertainty in the development of peak demand and demand flexibility, coal and nuclear phase-out policies, and the growth of renewable energy production have contributed to a shift in the perspective. As a result, security of supply has gained priority and capacity mechanisms are attracting greater support. In 2025, Germany announced plans to introduce a capacity mechanism by 2028. In the Netherlands, the Dutch Ministry of Climate Policy and Green Growth and the Netherlands Authority for Consumers and Markets (ACM) launched a debate on the introduction capacity mechanisms in 2025 [60]. This publication cited our work presented in chapter 2, which reflects the relevance of this research. In early 2026, the new Dutch government announced the introduction of a capacity market [61].

One of the primary objectives of the TradeRES project was to develop open-access tools for analyzing new market designs. Each member of the consortium contributed either an optimization or an agent-based model. The energy models were enhanced to represent additional energy sectors, flexibility resources, or to enable compatibility with other models. Besides enhancing the models, another goal was to combine the strengths of different models. VTT contributed a workflow management tool with scenario and data management that enabled the co-simulation of models. The TU Delft team, comprising my thesis supervisors Milos Cvetkovic, Laurens de Vries, and me, made a significant contribution to the investigation and proposal of a new electricity market designs aimed at improving resource adequacy. To investigate capacity mechanisms we applied a capacity expansion ABM called EMLab. Within this project, the original model was rewritten into Python to enable the co-simulation with other models.

At the beginning of the project, we aimed to implement a co-simulation between an optimization model, COMPETES, and an ABM, EMLabpy. As described in Annex B, this co-simulation presented several limitations, primarily due to high computational times. Capacity expansion ABMs involve dozens of iterative market clearing steps per simulation year. Each market clearing step simulated in COMPETES lasted around an hour and became longer with each simulation year, which made runtimes unfeasible.

We then pursued a co-simulation between EMLabpy and AMIRIS. The co-simulation with AMIRIS was possible, as it has a runtime of a few seconds. This co-simulation allowed for the simulation of realistic behaviour in both the short-term and long-term markets. Moreover, it enabled the simulation of combinations of multiple market designs, for example, renewable support schemes (feed-in tariffs, feed-in premiums, etc.) combined with capacity mechanisms. However, this was beyond the scope of the project and is recommended as future work.

Further research could also compare the results of various market designs simulated in ABMs against cost-optimal results. This was an initial objective of the project; however, a numerical comparison was not conducted due to the different scopes of the optimization models and the ABMs. For example, we simulated the Netherlands as an isolated system, whereas the optimization results were obtained on a Europe-wide scale.

Another objective of TradeRES was to develop a common database and a shared ontology from all the models of the consortium, enabling the exchange of data between models, regions, and scenarios. This was particularly challenging because most of the data was unique to each model. Nonetheless, we successfully established a shared database. TradeRES database's technological costs (investment, variable, and fixed costs), efficiency, technical lifetime, and fuel prices were applied in the co-simulation presented in this dissertation.

In addition to this dissertation, I made significant contributions to the following deliverables.

- D3.1: Performance specifications for a ~100% RES system. This deliverable was taken as the basis for the publication on adequacy indicators in Annex A.
- D4.5: New market designs in electricity market simulation models
- D4.7: Principles and usage of a multi-simulation electricity market tool
- D5.3: Performance assessment of current and new market designs and trading mechanisms for National and Regional Markets
- D6.2: User guide for TradeRES models and tools (D6.2.1)
- D6.3: Tutorial and webinar edited material

And participated in the following deliverables:

- D2.1: A database of TradeRES scenarios
- D3.5: Market design for a reliable 1̃00% renewable electricity system

2

Can an energy-only market enable resource adequacy in a decarbonized power system?

The chapter was originally published as I. Sanchez Jimenez, D. Ribó-Pérez, M. Cvetkovic, J. Kochems, C. Schimeczek, and L. J. de Vries: "Can an energy-only market enable resource adequacy in a decarbonized power system? A co-simulation with two agent-based-models" in Applied Energy 360 (2024) [62]

Abstract

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

2.1. INTRODUCTION

Early investment theory in power systems argued that spot pricing could lead to optimal investment incentives and decisions [63]. However, subsequent research has emphasized that the ideal conditions of perfectly competitive markets, including perfect information, absence of market distortions, risk aversion, and market power, do not exist in the power sector [64–67]. Several studies have suggested that the current market design may not deliver the required investments to ensure a transition to a future carbon-free power system [68–70]. In this study, we seek to determine to what extent an Energy-only-Market (EoM) can be expected to provide enough investment incentives for the market to reach system adequacy. Specifically, we analyze investments in an EoM and the propensity of this market design to guarantee cost recovery for all relevant technologies. We use an Agent-Based Model (ABM) to simulate myopic investment behavior and to evaluate the effects of weather year variability on the long-term performance of an EoM.

Future systems will rely on vRES and will require more demand-side flexibility than current ones to integrate them. Due to the variability of vRES, supply-side uncertainty increases. Recent studies have shown that in a market dominated by resources with near-to-zero marginal costs, the electricity price will be mostly set by carbon-free dispatchable backup generators, storage, and demand response [71, 72]. One of the main policy challenges for electricity markets is to design market rules that allocate resources efficiently and ensure the security of supply while minimizing costs. Analyzing a model of a future system can help policymakers make early adjustments to the market design, thereby reducing regulatory uncertainty for investors. Most studies of future systems are based on optimization models [73], which assume perfect competition, resulting in an equilibrium mix with the lowest system costs. However, prior research has shown that historically, actual generation expansion has not followed cost-optimal projections. For instance, [74] calculated a 9 to 23% discrepancy between optimal projections and actual generation expansion. Optimization models can incorporate multiple technical constraints and consider uncertainties to find an optimal solution. In contrast, alternative methods such as ABMs offer the possibility of investigating the impact of policies, considering limited information, and strategic decision-making. In general, generation expansion models don't intend to predict future capacity, but to give insights on factors that would impact the energy systems.

One of the reasons for the disparity between optimal solutions and real markets is that investors make investments according to expected revenues rather than making system cost-minimal decisions [75]. Moreover, lumpy investments and long lead times prevent the market from reaching an equilibrium [7]. Furthermore, investors may face uncertainty regarding competitors' decisions and future plans, commodity prices, technology costs, among others. As Tesfatsion [76] explains, actors in liberalized markets trade with imperfect information, limited foresight, and bounded rationality. Capacity expansion Agent-Based Models (ABMs) can mimic profit-seeking energy producers with myopic behavior and bounded rationality. Similarly, operational ABMs allow scheduling resources with a rolling time horizon, incomplete information, and no equilibrium. In our research, we simulate both investment and operational decisions with ABMs that allow us to analyze an energy system that is not necessarily in a long-run equilibrium.

We analyze a future electricity system, based in the Netherlands, with a co-simulation of two ABMS, AMIRIS [57] and EMLabpy, which is derived from EMLab [52]. EMLabpy is a long-term ABM that simulates the investment decisions of energy producers, while AMIRIS is a short-term ABM that simulates dispatch. EMLab, as a standalone model, cannot represent multiple types of flexibility, while AMIRIS does not have an investment algorithm. Hence, this co-simulation allows us to use the strengths of both models. In this way, we create a realistic simulation of investment under uncertainty while accounting for imperfect short-term market clearing. To reflect the flexibility of the future system, we execute the model on an hourly basis, considering the flexibility of demand and weather-dependent vRES. While there have been some investment and dispatch studies with the ABM model PowerACE for Germany [77], this is the first study that takes into account operational and investment decisions with bounded rationality and that integrates multiple flexibility options (battery storage, load shedding, and hydrogen electrolyzers), as well as model-endogenous decommissioning. To the best of our knowledge, this is also the first co-simulation of ABMs where the investment decisions are determined in an iterative process with a dispatch ABM.

Future uncertainties that will arise from weather patterns and their correlation with demand, as well as their impact on power prices and system adequacy, are not yet well understood. To evaluate the performance of an EoM under weather variability, multiple sequences of 40 random weather years are tested. Besides the commonly used reliability indicators, such as loss of load and energy not supplied, we analyze the volatility of electricity prices and market-based cost recovery, since these may also be early indicators of resource inadequacy [71]. We demonstrated that EoM will not be sufficient to ensure the security of supply in future 100% vRES systems and recommend exploring options for capacity remuneration mechanisms.

The rest of the research is organized as follows. Section 2.2 discusses the current literature around investment theory in the power system, agent-based models, and model coupling. Section 2.3 presents the relevant details of EMlabpy and AMIRIS and describes how these are applied in a co-simulation. Section 2.4 enlarges upon the used data and presents the case study. Section 2.5 shows the results from the analysis and their implications. Finally, section 2.6 concludes by summarising the paper's main findings.

2.2. Literature Review

2.2.1. Investment theory in power systems

According to the peak load pricing theory, in the long run, generators should recover their costs from scarcity rents [64]. A major impediment to the completeness of an electricity market, as described by Caramanis, Bohn, and Schweppe [63], has been the lack of fully flexible demand, which prevents the true Value of Lost Load (VoLL) during scarcity from being reflected in the market. Furthermore, regulatory price caps can enhance the missing money problem [65], which refers to insufficient revenues to cover the costs incurred by the generators. Market interventions, such as the introduction of caps on infra-marginal rents in response to the European energy crisis, and low participation in long-term markets have hampered a theory ideal market-led investment system [70]. Even if there were enough incentives, market participants might not perceive them. This is known as the missing market problem. Newbery explains that an EoM could work if the sources of the missing money and the missing market were removed [19].

In contrast to the theory of optimal investments, market failures that prevent an investment equilibrium are caused by a lack of risk allocation mechanisms, lumpy investments, long lead times, imperfect information, regulatory uncertainty, and uncertain interconnections, among others [7, 26]. All of these sources of myopic decision-making lead to a preference for low capital cost projects and prioritizing short-term profits over long-term projects as this can cause investment cycles and threaten the system's security of supply [52, 53, 78–81]. Underinvestment could result in large profits for generators at the cost of society. [68] Therefore, ensuring system adequacy, i.e. sufficient installed capacity to meet demand, can also prevent large money transfers that occur when prices are exceptionally high for an extended period of time [7], such as the situation that occurred in ERCOT during the 2021 Uri storm [82].

With more technologies with marginal costs close to zero, base-load technologies have suffered from reduced capacity factors. It is an open question if a decarbonized system could enable investors to recover their investments. Lately, several authors have recognized that CRMs might become more necessary as power systems shift from low capital costs and high capital costs to systems with low operational costs and high capital costs[83]. In addition, the volatility of electricity prices from late 2021 to 2023 has reinforced the inclination towards CRMs that can ensure the security of supply [84]. In a future market with volatile supply and flexible demand, as opposed to today's market with volatile demand and flexible supply, CRMs can engage the flexible demand to fulfill an important pillar of market design: affordability. Flexibility, which is defined as the ability to adjust supply and demand in response to changing conditions, will become a critical factor in enabling a decarbonized electricity market [68, 84].

2.2.2. WEATHER UNCERTAINTY

Around 2015, many gas plants in Europe were mothballed or prematurely closed as they were used less than planned. Besides carbon prices and fuel prices, a major cause was a lower demand than anticipated [85]. In a future electricity system, the weather will be a major source of uncertainty. vREs outputs can be very volatile, especially wind generation [86], leading to years with considerably larger vRES generation than others. Collins et al. [87] analyzed the impact of inter-annual weather variability in a Europe-wide optimization study and found the total generation costs variability would increase five-fold, from 2015 to 2050. Zeyringer et al. [88] compared investment decisions based on a single weather year against investment decisions by considering a ten-year horizon of different weather years. They found that optimizing for the longer time period increased the required installed capacity of flexible generators and total system costs compared to optimizing for each weather year individually; however, optimizing for individual weather years led to operational inadequacy and missing decarbonization goals. Price et al. [89] also analyzed how considering weather variability can result in distinct spatial deployment patterns.

Under an EoM, years characterized by high production will likely lead to lower electricity prices. If no hedging opportunities exist, investors may under-invest due to this uncertainty. This can aggravate one of the most important difficulties, coping with extreme weather periods when both wind and solar power generation are low or almost non-existent, a phenomenon also known as Dunkelflaute [90].

Regarding short-term uncertainty, vREs-dominated markets might exhibit high price volatility correlated to the availability of renewable generation. The addition of generation capacities of specific technologies can hamper their own business case due to generation autocorrelation and price depression [91]. However, demand flexibility might overcome this problem by becoming the price-setting instance in contrast to the current system where prices are determined by generators' marginal costs, thus improving the business case for vRES generators [92].

2.2.3. Simulating investment decisions with ABMs in electricity systems

Agent-Based Models (ABM) follow a bottom-up approach to modeling complex systems that involves simulating the behavior of individual actors (agents), such as generators, consumers, and other market participants, as well as modeling their interactions. ABM allows for the exploration of emergent phenomena that result from the interactions between agents and the study of the effects of environmental or individual agent behavior changes. ABMs have been used to study a wide range of electricity market design issues. By simulating agents with limited information, ABM allows studying generators with strategic behavior, their strategies participating in different markets as well as imperfect information in consumers' participation. Operational ABMs that solve Unit Commitment and Economic Dispatch (UCED) have been applied to study the impact of a high share of renewable energy and associated policies. For instance, Frey et al. [93] analyzed the risk of downward price dynamics in the German market premium scheme if vRES went from price takers to price setters.

Most capacity expansion models, also known as Generation Expansion Planning Models (GEPM), use optimization techniques representing a benevolent monopolistic system planner. Or, seen from the energy producers' perspective, market participants have perfect information about other agents' decisions, hence enabling a long-run market equilibrium (assuming perfect competition), where cost recovery is guaranteed [1]. This assumption is less realistic during an energy transition with an evolving capacity mix. Furthermore, optimization models usually incorporate a constraint for the supply to meet the demand and assign a high penalty for not covering all demand. In contrast, ABMs allow simulating myopic decisions where agents maximize their profits and no equilibrium is guaranteed [94], thus allowing insufficient generation adequacy and counteracting policies to be simulated. Furthermore, ABMs allow incorporating agents' behavior and market rules, for instance in the commissioning and decommissioning of power plants.

Previous investment ABMs have focused on questions regarding firms' heterogeneity, risk aversion, prospect theory in investment behavior [56], investment preferences [95], capacity mechanisms [25, 96] and the cross-border effects of these mechanisms [48] as well as the effect of CO_2 policies [55, 67]. More recent studies have included flexibility agents, e.g. [54] considers hydrogen in an ABM with an optimization model for

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

the dispatch, while [97] investigates the impact of battery expansion from prosumers. In [53], Anwar et al. present a detailed comparison of the latest generation expansion ABM models.

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

Oftentimes, energy system models use different methods to reduce the time series data and keep computational times feasible. Some options are to downsample data, cluster data, take representative hours/weeks by heuristics, or construct synthetic data [98]. Most studies on generation consider only one weather year, some studies make stochastic evaluations (i.e. [99]), and fewer studies consider investments based on an hourly time series analysis. Newer methods consider operational uncertainty with multi-horizon stochastic programming but still rely on representative days for investment decisions (i.e. [100]). Aggregating data can underestimate extreme values and loose chronology, which is relevant for adequacy analysis. Several studies have shown that reducing the scale to some hours or weeks per year results in inaccurate results and tends to underestimate the flexibility requirements [101]. Hoffmann et al. [102] present a summary of models that have aggregated data. They explain that grouping with a too low number of segments or typical days can introduce a systematic bias and propose an algorithm that finds a trade-off between these variables. Moreover, Helistö et al. [101] found that the impact of simplifying operational details is less than that of simplifying temporal representation, especially while modeling power systems with a large volume of flexible capacity. Flexibility will be a key enabler of a decarbonized power system, and thus it will be more relevant to consider hourly operational decisions to value storage and flexibility accurately. Therefore, it is relevant to base investment decisions considering a high temporal resolution. From the reviewed investment ABMs, only PowerACE makes an hourly analysis for investment decisions. To avoid losing accuracy, we also apply hourly modeling resolution in this study.

2.2.4. Co-simulation

Energy system simulations are becoming increasingly complex, needing higher temporal and spatial resolution, better uncertainty representation, and incorporating policy and human behavior [43]. Instead of expanding the scope of each model, co-simulation offers the possibility of exploiting the strengths of existing models and integrating exogenous information from other models to keep the computational complexity low. In a co-simulation, the independent simulators exchange their inputs and outputs for a given time step, and based on the received information each simulator progresses to the next step [103].

Soft-linking, on the other hand, involves utilizing the output of one model as the input of another model, but not necessarily in real-time. Soft-linking may be either unidirectional or bidirectional [101]. Most unidirectional soft-linkings have been performed to assess the operation of previously determined investment results and to incorporate the technical details into models with a broader scope [104]. Some studies have used unidirectional soft-linking to integrate spatially and temporally high-resolution results, [88] optimized the location of technologies with a power model from a less granular

GEPM.

In bi-directional soft-linking, the UCED model results are iteratively used to update parameters or add constraints to the GEPM [105]. For example, [106] soft-link the investment optimization model (TIMES) with an operational probabilistic model to reevaluate the capacity credits from different technologies and to reassess the security of supply of the future French power system. To the best of our knowledge, there has not been a study where the investment decisions are based iteratively on detailed dispatch results from another ABM.

Co-simulations can be facilitated by the use of workflow management tools. One of them is the Spinetoolbox [107]. Spinetoolbox is a graphical workflow management application that enables the coupling of energy models with distinct scopes and spatio-temporal resolutions. The tool manages the data flow between modules and the creation and visualization of workflows. Several studies have already used the Spinetoolbox to couple energy models. Among them, [108] formulates joint day-ahead energy and balancing capacity markets clearing, and [109] explores the interaction between long-term storage deployment and the expansion of the transmission capacity.

2.3. Methodology

2.3.1. Co-simulation of EMLabpy and AMIRIS

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

AMIRIS - developed by the German Aerospace Center (DLR) [57] - allows to simulate business-oriented bidding whereby policy incentives, e.g., for vRES support might be incorporated. In our study, AMIRIS is applied with a rolling weekly dispatch scheduling of flexible agents (see 2.3.2). EMLab (Electricity Modelling Laboratory) is a model that enables the investigation of policies on generation expansion and other policies [52]. In EMLab, investment decisions are based on the expected returns from a simplified dispatch algorithm with a segmented load duration curve. Although it can model storage, the demand is aggregated into a segmented load curve with a limited representation of flexibility [110]. In contrast, AMIRIS offers the representation of several flexible technologies, such as electricity storage, electrolyzers, or heat pumps. Hence, through co-simulating we combined the strengths of both models.

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

2.3.2. WORKFLOW OVERVIEW

Figure 2.1 depicts an overview of the employed workflow. Figure 2.14 in the appendix shows the workflow setup in Spinetoolbox. Each module is explained in detail in the following subsections.

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

Spinetoolbox allows to manage multiple databases to store different input and output data. In this workflow, the EMLabpy-database stores the data to run all modules, while the AMIRIS database stores the yearly dispatch and market results. The market results are used in the financial-results module (see in appendix 2.15 the data workflow).

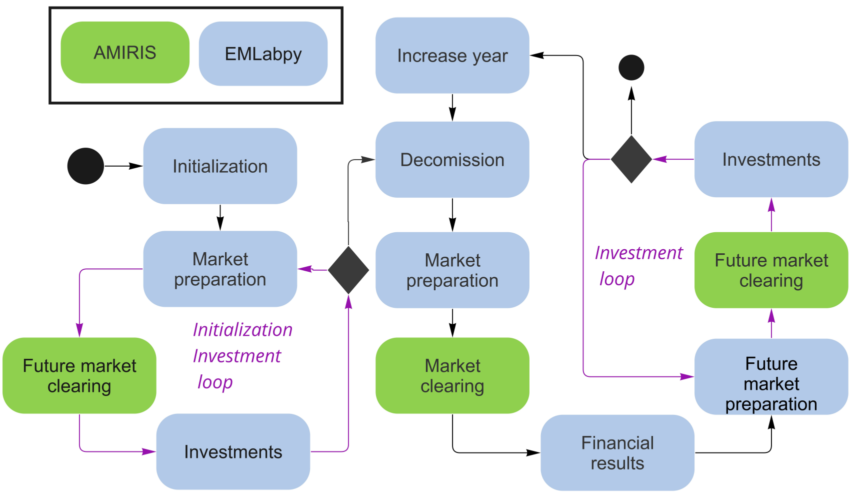

Figure 2.1: Overview of the co-simulation methodology

INITIALIZATION INVESTMENT LOOP (IN EMLABPY)

We solve a brownfield problem. If there is insufficient generation capacity at the start of a simulation, severe shortages may occur in the first simulated years. For this reason,

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

an initialization investment loop is executed to account for investment decisions made before the simulation.

Decommission (in EMLabpy)

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

Market preparation (in EMLabpy)

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

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

Market dispatch (in AMIRIS)

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

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

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

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

FINANCIAL RESULTS (IN EMLABPY)

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

INVESTMENT DECISIONS (IN EMLABPY)

Investment decisions are based on the investors' future expectations which are derived from the AMIRIS future market outcomes and the technical and financial conditions, as shown in Figure 2.2. First, EMLabpy evaluates the physical limitations of each technology. If the capacity limits per technology, as specified in 2.11, have not been exceeded, the NPV is computed for each technology as shown in algorithm 1, and the technology with the highest positive profitability expectation is chosen for investment (see Figure 2.2).

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

To reduce run time, 1 MW of each investable technology is evaluated on the future market. If the result of this 1 MW is positive, larger capacities are installed after a technology is chosen, as specified in the table 2.10. To prevent overinvestments, as the NPV of the evaluated technologies approaches zero, the tested capacity is increased for subsequent investment iterations.

$$A = \frac{Debt}{\frac{1}{i}(1 - \frac{1}{(1+i)^{T_{\mathrm{EL}}}})} \tag{2.1}$$

$$NPV = \sum \frac{CashFlow_t}{(1+\rho)^t} \tag{2.2}$$

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

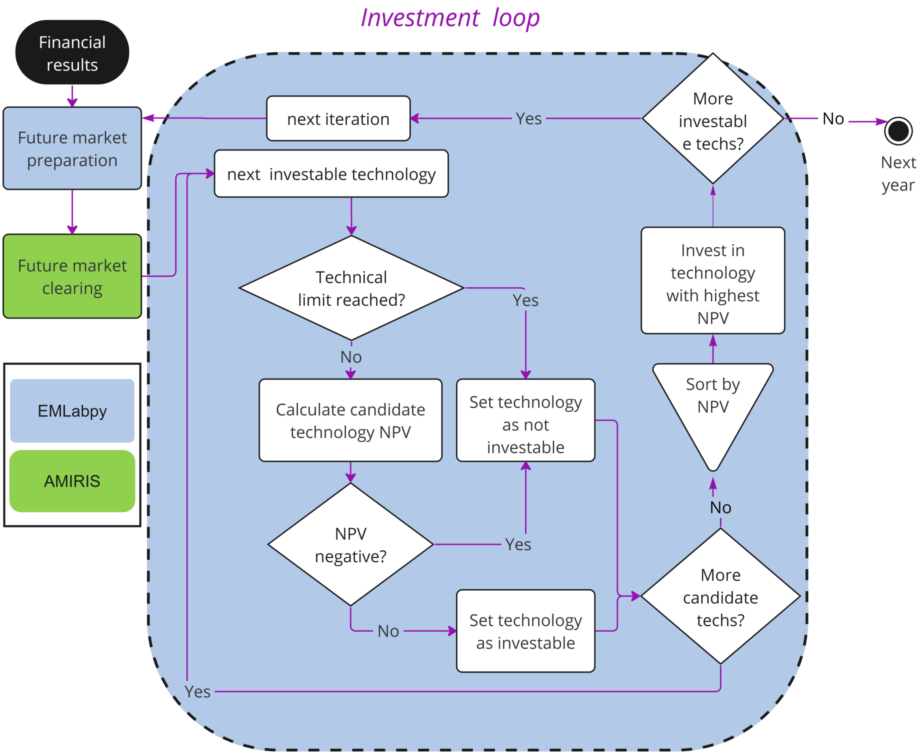

Figure 2.2: The investment module can be located in the workflow overview 2.1.

Algorithm 1 Investment algorithm

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function < CALCULATE NPV>
  ER = (1 - DR)
  Debt = DR * CAPEX
  DP = (CAPEX * ER) / T_C
  Calculate A, using 2.1
  for $year \in \{0 \ldots T_C + T_{EL}\}$ **do**
    if then $year < T_C$
      $CashFlow[year] = -DP$
    else
      $CashFlow[year] = Rev - FC - VC - A$
    end if
  end for
  calculate NPV using 2.2
end function

2.3.3. MODEL VERIFICATION OF THE INVESTMENT ALGORITHM

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

2.4. EXPERIMENT DESIGN: SIMULATING A FUTURE DECARBONIZED POWER SYSTEM

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

2.4.1. DATA

FUTURE WEATHER DATA

Technological advancements, such as the deployment of higher wind turbine hub heights, efficiency improvements, and longer blades are expected to increase the full load hours of wind and solar energy. Offshore wind farms have been and will continue to be placed further from the shore, being able to capture a higher wind speed spectrum. To scale the historical Capacity Factor (CF) time series, an algorithm is applied to increase the full load hours per technology to future expected capacity factors, according to IRENA [111] and IEA [112], see table 2.11. The code for the augmentation of the profiles can be found in [113]. The historic weather profiles are taken from the Merra2 database [3].

LOAD REPRESENTATION - WEATHER-DRIVEN DEMAND

We assume that household, commercial, and electric vehicle demands are triggered by consumer routines (weekdays), whereas heat pump demand is driven by the outdoor temperature. To determine the heating demand according to the weather and its correlation with vRES generation, we correlate the historical data for temperature with the hourly space heat requirements for the years (2008-2016) based on [115]. Due to the lack of data for the rest of the years (1980-2007 and 2017-2019), we perform a linear regression considering the hourly variations in heating demand. m_h and n_h are the slope and intercept calculated for every hour of the day. The regression for space heat demand is performed for temperatures under 18 °C. SHR_t represents the calculated space heat demand (MW) demand at time t and is always a non-negative value.

$$SHR_t = m_h \cdot T_t + n_h \tag{2.3}$$

We assume a fully electrified space heating demand with Air Source Heat Pumps (ASHP) and Ground Source Heat Pumps (GSHP). Their Coefficients Of Performance (COP) correlate with existing temperatures from the same database [115], but without considering hour-of-the-day differences. We considered ASHP and GSHP with radiators

[3]www.renewables.ninja [86, 114]

2

and excluded high temperatures to achieve the highest correlations. The correlation for ASHP is done with temperatures below 13 °C, while for GSHP below 15 °C.

$$COP_t^{GSHP} = m^{GSHP} \cdot T_t + n^{GSHP} \quad \forall COP^{GSHP} \quad \in 2.5 < COP^{GSHP} < 6.32 \tag{2.4}$$

$$COP_t^{ASHP} = m^{ASHP} \cdot T_t + n^{ASHP} \quad \forall COP^{ASHP} \quad \in 1 < COP^{ASHP} < 4.06 \tag{2.5}$$

Finally, we obtain the electricity consumption demand for space heating SHD_t by considering their hourly COP and the market shares (MS) of 0.6 for ASHP and 0.4 for GSHP, following [116] for households.

$$SHD_t = MS^{ASHP} \cdot SHR_t / COP_t^{ASHP} + MS^{GSHP} \cdot SHR_t / COP_t^{GSHP} \tag{2.6}$$

Flexible load representation - Hydrogen, and industrial heating demand

While the focus of our research is on electricity market design, we make some assumptions about the composition of the future energy system. The production and storage of hydrogen are expected to provide an important function for periods with insufficient vRES. In Europe, hydrogen will be primarily used to decarbonize hard-to-abate sectors such as the industrial and transportation (e.g., maritime, aviation) sectors [117, 118]; therefore, we assumed that electrolyzer operational costs and storage costs will be mainly borne by sectors other than the electricity sector. As a result, we do not simulate hydrogen storage investments or operations, as we only consider the production of green hydrogen and its use in the power sector.

The electricity demand to produce hydrogen is modeled as flexible (limited to the available electrolyzers' capacity). Hydrogen production is interrupted if the electricity price exceeds 33.4 €/MWh, which corresponds to the expected future market price of hydrogen (45 €/MWh [119]) times the efficiency of electrolysis (74%). Thus, hydrogen is produced when vRES production is sufficiently high and power prices are low. We simulated a completely flexible hydrogen production by simulating electrolysis as a load-shedding unit. As a simplification, we consider constant hydrogen prices under the assumption that in the future, there will be sufficient storage capacity and a well-established hydrogen market. In reality, prices will vary depending on several factors, including vRES generation, the diversification of hydrogen sources, the capacity and adaptability of electrolyzers, the availability of hydrogen transportation, imports, storage, and the interaction between the electricity and hydrogen markets.

We model industrial heating as a price-capped load-shifting agent (see section 2.3.2). The yearly flexible industrial heating demand is extracted from COMPETES, which takes as an input ENTSO-E data [119]. If electricity prices are low, industrial demand is met with electric furnaces; otherwise, demand is shed or natural gas is used. Hence, the price cap for the industrial demand was 48.6 Euro/MWh.

For the rest of the demand, the ENTSO-E demand time series is scaled according to the 2050 global ambition scenario from the TYNDP [119] (6.1 TWh EVs and 144 TWh inflexible demand). Likewise, the electric vehicle profile load is based on 2015 but is scaled to 2050 to account for the projected fleet size. The EV profiles are modeled using the Charging Profiles of Electric Vehicles model (ChaProEV) [120], which uses electric vehicle parameters, user activities, and locations to generate charging profiles. The demand for heat pumps is included, as described in subsection 2.4.1.

Table 2.1: Summary of flexibilities in the model

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

LOAD REPRESENTATION - LOAD SHEDDING

Currently, AMIRIS has a limited capability of modelling competing load shifter strategies. To account for a high demand response, we model different load shedding clusters. Based on literature about load shedding in The Netherlands and Europe [121–123], we assume that 20% of the conventional demand has a lower VoLL than the market cap (4,000€/MWh). This sheddable demand includes EVs and heat pumps, but excludes industrial heating and electrolyzers demand. In summary, we model a highly flexible system in which 51% of the loads are sheddable (45% is the sheddable demand from electrolyzers and 6% has a lower VOLL than the market price cap), 13% of the loads are shiftable (from industrial heat), and only 35% are inflexible (see Table 2.2).

Table 2.2: Load flexibilities percentage from total demand

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

INITIAL POWER PLANTS

The initial 2050 generation capacity mix of a stylized future Dutch system is extracted from the results of the optimization model COMPETES [122]. COMPETES is an optimization model used by the Dutch government in the country's Energy and Climate Plans [124]. The initial capacities and flexible resources resemble those planned in the Energy and Climate Plans. As nuclear technology costs are highly uncertain and its investments remain political, these tend to be centrally planned. For this reason, nuclear capacity is set constant according to COMPETES results. Similarly, the electrolyzers capacity is also taken from COMPETES capacity of 41 GW, due to its better representation of sector coupling. From these initial capacities, we run the EMLabpy-AMIRIS workflow for 40 weather years with constant prices, temperature-dependent demand profiles, and

Table 2.3: Scenarios

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

capacity factor profiles (both will be referred to as weather profiles), achieving a stable capacity based on ABMs, which we then use as a base for the simulations.

The optimization and the ABM models resulted in different capacity mixes for several reasons. COMPETES makes a perfect foresight dispatch for a whole year, while within AMIRIS, flexibility agents create weekly schedules. AMIRIS currently has a limitation for simulating the flexible operation of flexible sources simultaneously (see Figure 2.3.2). The operation of combined heat and power plants, Power-to-H_2, gas-to-H_2, and H_2 storage as well as demand side response can be optimized within COMPETES, but not in AMIRIS. However, the largest difference is caused by the absence of imports/exports in the ABMs. Cross-border trade can greatly contribute to the reliability of neighboring countries resulting in less installed capacity. We simulate the Netherlands as an island because modeling all dimensions of power system models (space, complexity, and time) would be too computationally intensive for the purpose of this study.

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

2.4.2. SCENARIOS

In all simulations, investment costs, fuel, and CO_2 prices are constant (see Tables 2.8, 2.9 and 2.10) present the rest of the data used in each scenario. In all simulations, we considered one agent investor, as the purpose is to study weather impact rather than dynamics with different types of investors. Each simulation is executed for a simulation horizon of 40 years. We use a combination of scenarios to study the impact of weather variability, the impact of basing investment decisions in different weather years, and the impact of hydrogen prices on future system adequacy. Table 2.3 presents an overview of the simulations.

WEATHER IMPACT SIMULATIONS

It is our impression that energy producers tend to estimate future cash flows by multiplying the expected energy yield times the expected electricity prices, either for a single scenario or for a handful of electricity price estimations, as described in [125]. Price cannibalization[4] can be estimated using a regression equation that represents the relationship between an increasing share of vRES and decreasing prices, as explained in

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

[126].

In EMLabpy, to resemble a risk-neutral agent (who considers P50 for investments), investment decisions are based on a weather year with a median renewable production. An alternative is to select the year in which the market revenues are median, but these revenues are highly dependent on the number of scarcity hours. A fixed capacity mix from ABMs (as described in Section 2.4.1) is evaluated with 40 yearly vRES profiles (augmented from 1980 to 2019) and the corresponding demand profiles. The year with a median renewable energy production is 2004, which we select as the representative year.

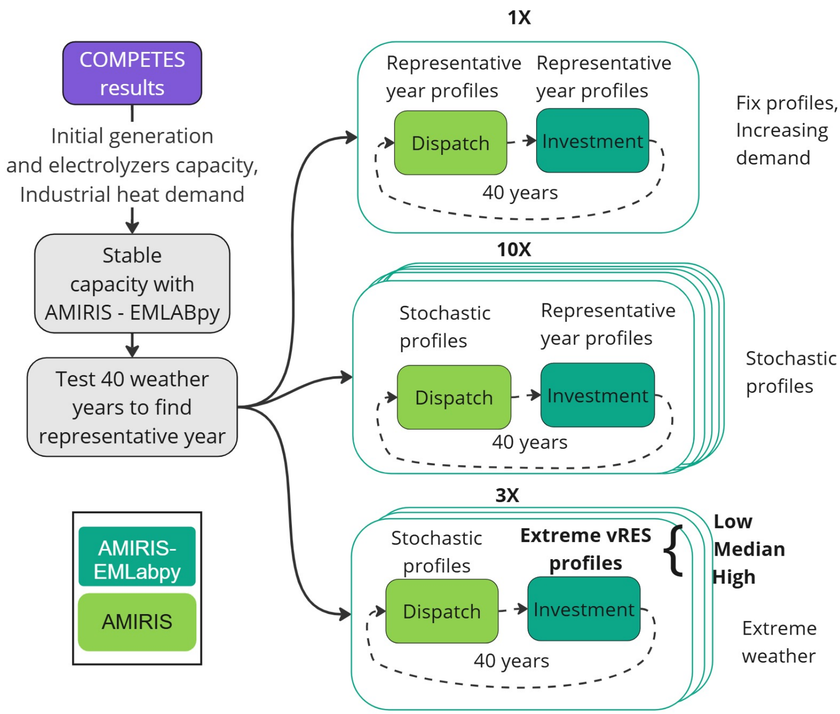


Figure 2.3: Stochastic profiles simulations' workflow. This is a more complete version than the figure presented in the original publication.

In the long run, dependence on weather may cause higher uncertainties than demand growth. Both uncertainties are compared as follows. In the Baseline scenario (B), the actual weather profiles serve as the basis for investors' decisions, granting them perfect foresight. In a second benchmark scenario, the demand and weather profiles remain constant but demand presents a stochastic Increased Demand (ID). In this scenario, demand increases with a triangular trend, as done in [79] (min= 0.99, max=1.03, and mode=1.02). The future demand is estimated with simple linear regression from the last three years.[5] Finally, in the Stochastic Profiles (SP) scenario we run ten simulations with no increase in demand, but with varying weather profiles. Every year, the market clearing is based on randomly selected historical weather profiles, whereas investment decisions are based on a representative year, as shown in Fig 2.3.

INVESTMENTS BASED ON EXTREME WEATHER

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

HYDROGEN PRICE

Finally, we simulate a scenario where the hydrogen price was double than the one used in the rest of the simulations, which was based on the ENTSO-E global ambition scenario [119].

2.4.3. KEY PERFORMANCE INDICATORS OF THE RESULTS

To compare the results of the co-simulation we use the following Key Performance Indicators (KPI) and their inter-annual variability (coefficient of variance). The KPIs are used to assess the overall system and performance by technology.

- Adequacy KPIs
  - Energy Not Served (ENS) (MWh/year): Energy that is not supplied due to insufficient capacity resources to meet the inflexible demand. [6]
  - Loss Of Load Expectation (LOLE) (hours/year): Number of hours in which resources are insufficient to meet the demand
  - Hydrogen production (MWh): Power consumed by electrolyzers to produce hydrogen
- Financial KPIs
  - Monthly average electricity prices (€/MWh)
  - Weighted averaged yearly electricity prices (€/MWh)

$$WAVGprices_y = \frac{\sum_{t=1}^{t=8760} prices_t \cdot Generation_t}{\sum_{t=1}^{t=8760} prices_t} \tag{2.7}$$

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

$$CostRecovery = \frac{Rev}{CapEX + VC + FC + A} \tag{2.8}$$

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

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

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

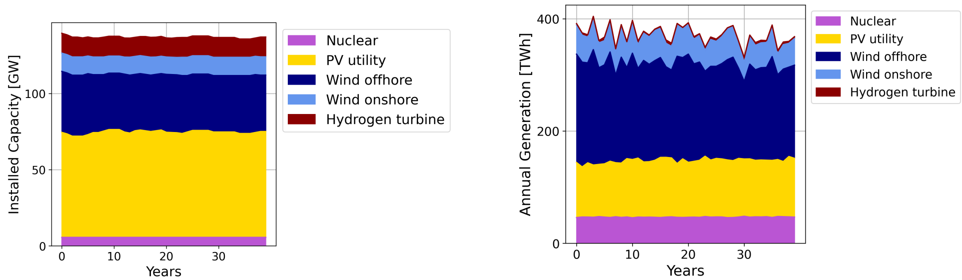
2.5. RESULTS AND DISCUSSION

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

2.5.1. IMPACT OF WEATHER VARIABILITY

INSTALLED CAPACITY

Since the investment algorithm was based on the same weather year throughout the whole simulation, the generation mix remained relatively constant (see Figure 2.4a). Investment costs for wind offshore are expected to be 4 times larger than those of PV (Wind offshore capital costs are 1,444 €/kW compared to PV capital costs of 350 €/kW, see **??**), as a result, solar PV energy composed the largest proportion of the portfolio. In contrast, offshore wind total generation was 30% higher than solar generation, as it has a higher capacity factor (Wind offshore capacity factor is 51%, in contrast to 16% from solar PV).



(a) Annual installed capacity per technology

(b) Annual generation per technology

Figure 2.4: Yearly installed capacity and generation by energy technology

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

ELECTRICITY PRICE DYNAMICS

Nowadays the price in electricity markets is mainly driven by generators's marginal costs. In future power systems, the disparity between the near-to-zero marginal cost of vRES and that of fuel-based technologies will continue to exist. However, electricity prices will be mostly set by flexible demand. Hydrogen will be produced when prices are below the hydrogen market price. Similarly, the industrial heat demand will be satisfied when prices are below the costs of using natural gas boilers. Figure 2.5 illustrates the price duration curve for one year, with each color representing the price-setting generator or demand. Electrolyzers and industrial heat demand set the price most of the time.

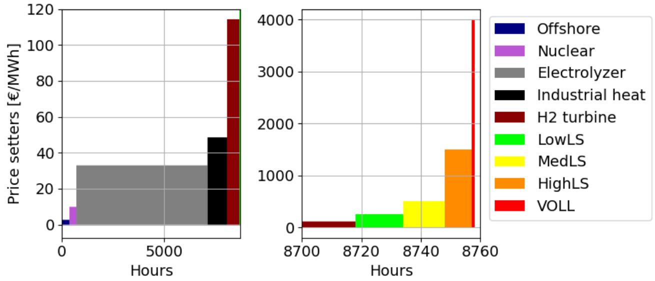


Figure 2.5: Price setting technologies in year of a SP simulations.

Although we modeled a highly flexible system, there was not sufficient investment in flexible resources to prevent shortages in years with high demand and low vRES production. During the winter, heat pumps increased demand during periods of low renewable energy production, resulting in involuntary load-shedding despite a decrease in hydrogen production (see Figure 2.6). This occurs even though the industrial load was totally flexible. In practice, industrial processes may not be able to completely switch between using electricity and other fuels, nor may they be able to shift the load for extended periods of time.

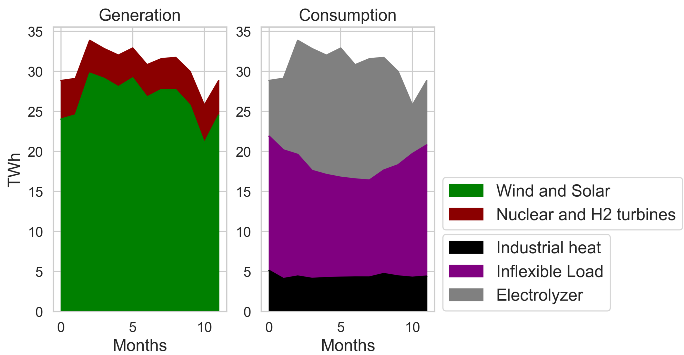


Figure 2.6: Monthly generation and consumption of a SP simulation

Analyzing the monthly average electricity prices, we observed a large disparity between the winter months and the rest of the year. For instance, in June average electricity prices were 33.9 €/MWh, whereas in January the average went up to 71.2 €/MWh, (see Figure 2.7). Extreme average monthly prices above 150 €/MWh were repeatedly seen as a result of a correlation of low vRES and low temperatures. This indicates that future vRES-based power systems will require long-term storage (both thermal and electrical), demand-side flexibility, and mechanisms that incentivize them.

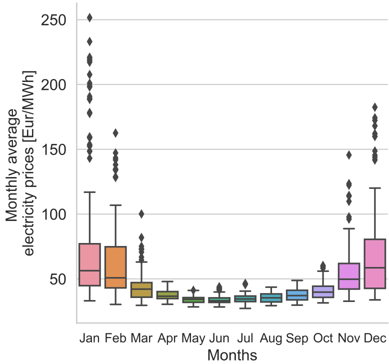


Figure 2.7: Monthly average electricity prices of stochastic-profiles simulations

ADEQUACY KPIS

The adequacy of future systems will be vulnerable to weather variations. While in the baseline scenario and the increasing-demand scenarios, the average LOLE was 3 hours per year, in the SP scenario, shortages increased to an average of 6.7 hours (see Table 2.4). This is more than the current LOLE standard in the Netherlands, which is 4 hours per year [127]. The average LOLE in SP scenarios was almost twice the current standard, but in the worst year, the shortages went up to 48 hours. This reveals that an EoM design might hinder the system's adequacy as the capacity will not be able to guarantee sufficient supply in the years with low vRES.

Shortages were the main cause of higher electricity prices and cost recovery. As shown in Figure 2.9, the years with the highest shortages and ENS were also the years with the highest electricity prices and years with the highest cost recovery. In contrast, years with high vRES energy yield worsened the cost recovery. The yearly cost recovery of the total system consists of market revenues and costs, including down payments and loans. In the years when there were more power plants under construction, down payments caused a minor decrease in cost recovery, as shown in Figure 2.8. Note that a share of loans remained constant, which corresponds to the loans of nuclear plants that were not decommissioned.

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

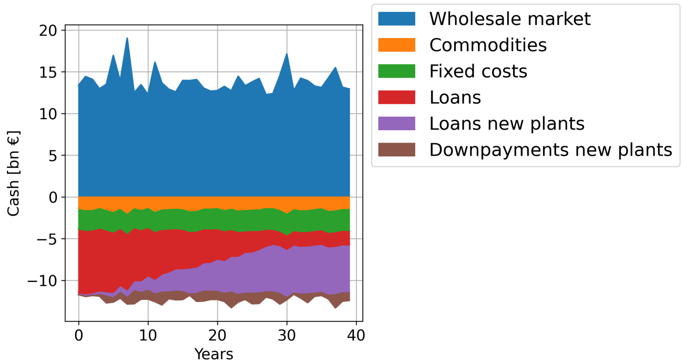


Figure 2.8: Total revenues and expenses in a SP simulation

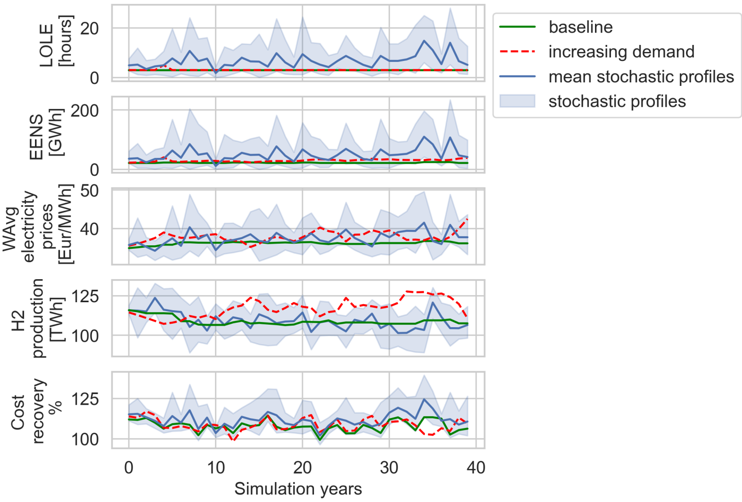


Figure 2.9: KPIs in the Baseline scenario, in the ID scenario, and the SP scenario in the realized dispatch.

Financial KPIs

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

Table 2.4: Adequacy and Financial KPIs of simulations about the impact of weather variability.

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

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

In years with low renewable yield and high electricity prices, hydrogen production was relatively low. The electrolysis production in the stochastic-profiles scenario ranged between 94 and 148 TWh and its volatility (11%) was five times that of the fix-profiles scenario (2%). In these simulations, a fixed hydrogen price was assumed; however, the hydrogen price will be very dependent on the H_2 interconnections, storage capacities, and the flexibility of other sectors. Furthermore, the volatile electrolyzers' operation would impact the price of hydrogen. If hydrogen resources are insufficiently diversified or interconnections limited, a year with low renewable energy would result in lower H_2 production and high hydrogen prices. As hydrogen turbines would be dispatched at a higher cost, electricity prices could rise even further.

Calculating the IRR over the entire lifetime of new power plants (for plants that are built and decommissioned during the simulations), H_2 turbines presented the highest and most volatile returns, followed by wind onshore, offshore, and PV (see Figure 2.10). Since dispatchable technologies were operational during most scarcity events, they generated the majority of their revenue during these instances. In contrast, vRES did not always operate during scarcity hours and therefore did not receive these scarcity rents. For this reason, the inter-annual volatility of vRES's profits was smaller.

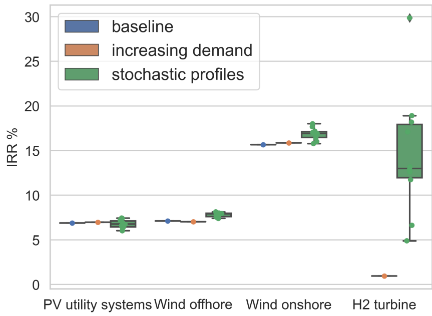


Figure 2.10: IRRs of new plants under SP scenarios.

As described in the previous section, the total cost recovery was higher in the ID scenarios and even higher in the SP scenarios. Nevertheless, the hydrogen turbine had remarkably high volatile returns. In one simulation, the hydrogen turbine operational profits were negative for five consecutive years [7] (see Figure 2.11), and also very high in some years. The profitability of all technologies, particularly that of hydrogen-fuelled technologies, can be even more volatile as hydrogen price is unlikely to remain constant. This poses the question of whether financial instruments would exist for a technology that may be unprofitable for some consecutive years. Furthermore, the nuclear plants' operational profits were consistently the most negative and volatile (see **??**). This illustrates that in a highly flexible system, where electrolyzers with low opportunity costs largely determine prices, base load technologies may struggle to recoup their expenses.

Out of the vRES technologies, solar energy showed the lowest average profits, which is due to the cannibalization effect. The investment algorithm frequently invested in this technology, but subsequent investments diminished their profitability. The anticipated high profits from onshore wind would have encouraged additional onshore investments, but its technical capacity limit (12 GW) [128] was reached. Hence, it presented the highest returns among the vRES technologies.

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

2

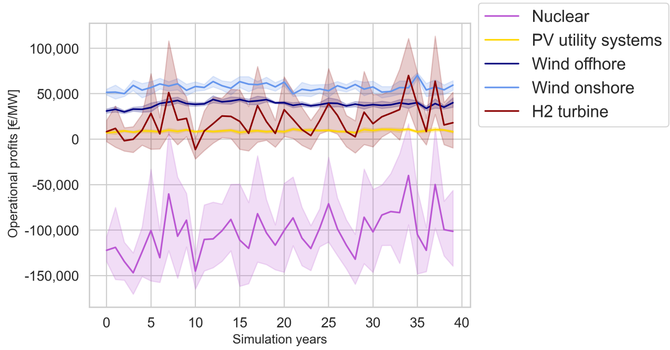


Figure 2.11: Annual operational profits per MW in the stochastic-profiles scenario

2.5.2. INVESTMENTS BASED ON EXTREME WEATHER YEARS

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

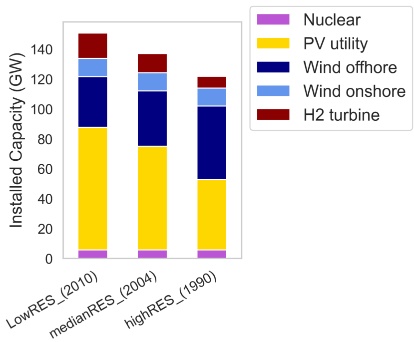


Figure 2.12: Last simulation year installed capacity in scenarios where investments were based on extreme weather years.

In EH scenario, the installed capacity was 121 GW, i.e. 11.1% less capacity than considering the median vRES (see Figure 2.12). The reduced investments caused scarcities (37.8 hours on average), high weighted average electricity prices (44 €/MWh on average), and led to a high-cost recovery (133% on average). In this case, the hydrogen turbine generators obtained extremely high returns (see Table 2.6), due to the frequent shortages. Alternatively, if investment decisions were based on an EL year, investments added up to 150 GW, i.e. 9.9% more capacity than with median vRES yield. The weighted average electricity prices were lower (37.4 €/MWh on average), and market revenues were insufficient to cover the costs (cost recovery is 98% on average). In this scenario, only wind energy generators recovered their investments, and the wind onshore presented the highest returns (see Table 2.6). The algorithm would have invested more in this profitable technology but the technical potential was quickly reached.

The offshore wind energy yield was the most variable among vRES technologies, so considering a year with high renewable energy yield led to a portfolio with a higher share of wind offshore, even if the total capacity was smaller. Investing based on a high-vRES yield resulted in the installation of 49 GW of wind offshore, compared to 37 GW when using the median return profile and 34 GW when using the lowest return vRES profile.

Electrolyzers' activation depended on the number of hours in which the electricity price was less than the market price of hydrogen. In the simulation with high-vRES, offshore wind energy share in the capacity mix was greater, resulting in more hours with low electricity prices and thus, more arbitrage opportunities for electrolyzers (see 2.5). For this reason, hydrogen production increased in the high-VRES simulation, even though less capacity was installed overall.

Table 2.5: Investment KPIs considering extreme weather years

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

2.5.3. HIGHER HYDROGEN PRICE

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

Table 2.6: Average IRR per technology with extreme weather investments

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

capacity of electrolyzers will ultimately be influenced by the hydrogen price.

On one side a higher hydrogen price incentivized more investments, especially in wind offshore generators, which had a broader energy generation distribution than solar energy. The technical limit of wind offshore (70 GW) was reached in contrast to the 37 GW with lower hydrogen price, which raised the average profitability of offshore turbines from 8 to 15%. On the other side, it decreased the profitability of hydrogen turbines, deterred investment in these technologies, and exacerbated shortages. 10 GW of hydrogen turbines were installed, in contrast with the lower hydrogen price simulations, where 13 GW were installed (see Figure 2.13)

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

Table 2.7: Investments KPIs with double hydrogen price

		Base	**Double H2 price**
Installed capacity	GW	137	172
ENS	Avg [MWh]	50888	71214
	COV	123%	93%
LOLE	Avg [hours]	6.8	9.5
	COV	115%	89%
Yearly weighted average electricity prices	Avg [€/MWh]	37.4	43.4
	COV	14%	16%
Monthly average electricity prices	Avg [€/MWh]	45.7	57.1
	COV	49%	42%
Hydrogen production	Avg [TWh]	148	273
	COV	12%	8%
Cost recovery	Avg [%]	111.8	127.2
	COV	10%	10%

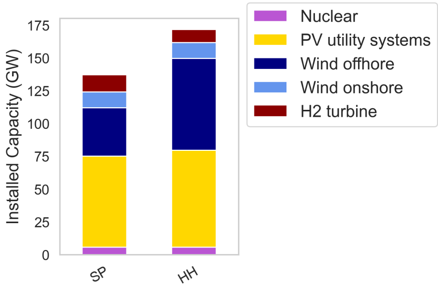


Figure 2.13: Final Capacities of one SP and high hydrogen price simulation

2.5.4. Policy implications

Our results show that future vRES-based energy systems with an EoM design will be susceptible to weather volatility. The uncertainty regarding energy supply will be larger than the current uncertainty regarding demand levels. This can cause large shortages and high inter-annual revenue volatility. As a result, investors can be expected to have difficulty financing investments with high CAPEX, as there will be a poor business case for generation and energy storage units that are only needed in unfavorable weather years. Moreover, as Neuhoff [129] explains, uncertain returns increase financing costs, decrease investments, and diminish consumer welfare. Therefore, the adoption of revenue-stabilization mechanisms is necessary both for achieving security of supply and for reducing the cost to consumers.

Regarding hydrogen production and system integration, Mikovits et al. [130] modelled a system where the wind power capacity covers on average the power demand for electrolyzers and found that a large capacity of wind turbines and electrolyzers can decrease the need for backup capacity. We found that the installed capacity of offshore energy will depend on the hydrogen price, and a larger share of wind offshore increases hydrogen production. However, we observed that the volume of dispatchable generation capacity ultimately determined the number of shortages.

Finally, a future market design should incentivize sufficient investment but also limit earnings in the case of prolonged high prices, as consumers suffer as much from the high prices during a prolonged shortage period as from the outages themselves. We observed that price spikes and adequacy requirements predominantly occur during cold months when heating needs arise. The significant monthly and inter-annual price variations due to weather volatility present another important challenge of the energy transition, which is consumer price protection. Highly volatile monthly electricity prices also highlight the need to ensure sufficient seasonal storage, demand flexibility, and energy system integration with energy vectors such as hydrogen. Market design can facilitate the investment of technologies with high capacity factors through CRMs. However, as [131] recognized, the estimate of the contribution of each technology to peak load, the estimate of values of lost load, the probability of peak load, and the probability of generation availability are becoming increasingly challenging.

2.5.5. MODEL LIMITATIONS

In a future system, cross-border transmission can greatly influence the capacity that is required to meet adequacy standards, as imports can mitigate scarcity events. Astier et al. [131] demonstrate that reliability standards can lead to socially optimal results only if adequacy assessment assumptions are coordinated between neighboring countries. Ignoring cross-border trade can lead to overestimating electricity prices ([128] quantifies this effect to up to 40%), but it is uncertain to what extent countries are willing to rely on neighboring power supplies to ensure adequacy. However, in our co-simulation of two ABMs, modeling multiple European countries would have been computationally infeasible. Therefore, we did not consider internal or cross-border transmission constraints. Furthermore, the model does not consider sector coupling, resulting in a capacity mix different from the optimization results.

Finally, it is worth mentioning two additional factors not analyzed in this study that could further compromise the reliability of the system. Nowadays, a minority of outages are caused by insufficient installed capacity, while distribution and transmission inefficiencies and the correlation of extreme weather events with infrastructure failures have been the main reasons for the most serious shortages [82]. Furthermore, extreme weather events are expected to intensify due to climate change effects. With fatter distribution tails, building sufficient backup capacities will also be more relevant.

2.5.6. LESSONS FROM CO-SIMULATING

Co-simulating can be time-intensive, as it requires careful coordination and data management among the involved models. However, it also allows the utilization of a subset of the data in each module as needed. As portions of the problem are divided, this can keep the computation size manageable for simulations spanning multiple decades. Moreover, developing models in a modular manner can allow reusability and parallel model development. The ABMs applied here are built in a way to allow coupling with other models [8].

2.5.7. FUTURE WORK

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

2.6. CONCLUSIONS

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

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

tem. We performed our analyses for an energy-only market, i.e. a market in which the price of energy drives investment.

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

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

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

2.7. APPENDIX

Table 2.8: Technology costs at year 2050 [119, 132]

	Investment costs [€/MW]	Variable costs [€/MWh]	Fixed costs [€/MW/year]	Efficiency [%]
Lithium ion battery	€ 1,020,000	1.8	800	0.90
WTG offshore	€ 1,444,000	3	24700	
PV utility systems	€ 350,000	0	7600	
PV residential	€ 688,000	0	11000	
WTG onshore	€ 1,127,000	1.35	12900	
Biomass CHP	€ 2,040,000	1.9	50000	0.31
Hydrogen turbine	€ 435,000	1.5	8700	0.40
Nuclear	€ 6,000,000	4	100000	0.29

Table 2.9: Fuel prices at year 2050 [119, 132] Global ambition. H_2 price is the renewable H_2 imports price in [119]

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

Table 2.10: Technology data

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

Table 2.11: Capacity factors [111, 133] and technology potential for vRES [128, 134]

	Min capacity factors [%]	Max capacity factors[%]	Technology potential [GW]
WTG onshore	32	58	12000
WTG offshore	43	60	70000
PV residential	15	18	26964
PV utility systems	15	18	82099
Biofuel			12040

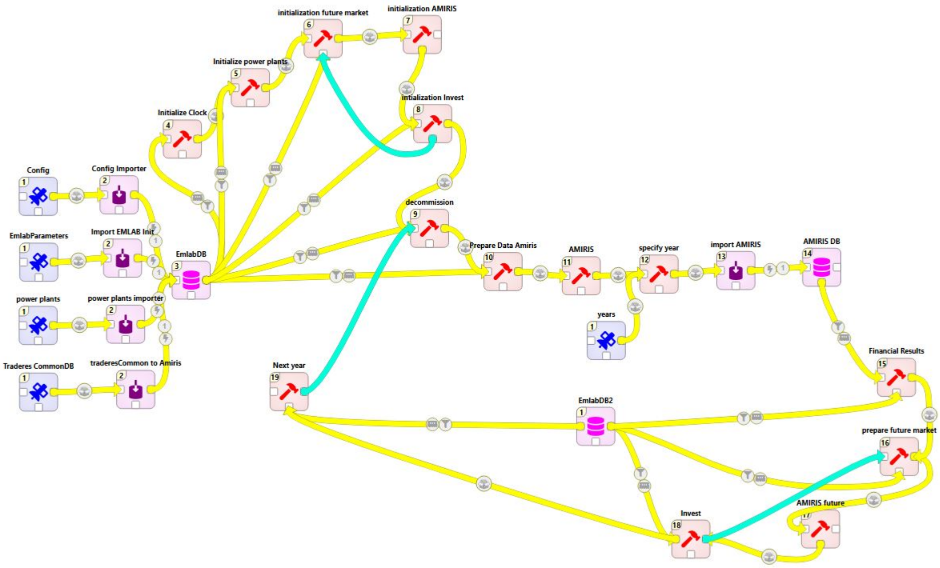


Figure 2.14: Workflow in Spinetoolbox

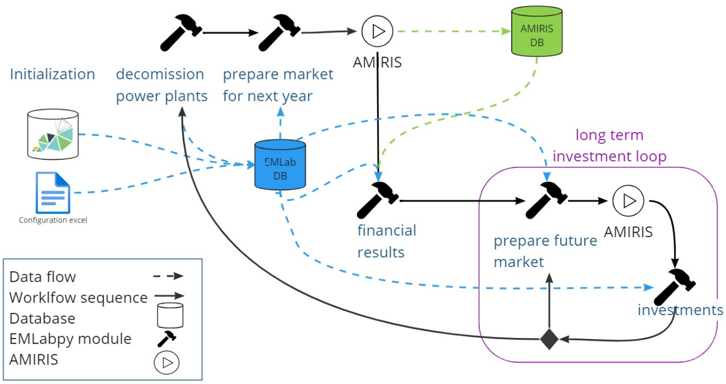


Figure 2.15: Data workflow

Table 2.12: Operational profits per MW by technology

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

Table 2.13: Yearly average IRR per technology

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

3

Capacity Remuneration Mechanisms for Decarbonized Power Systems

The chapter was originally published as I. Sanchez Jimenez, K. Bruninx, and L. J. de Vries: "Capacity Remuneration Mechanisms for Decarbonized Power Systems" in Applied Energy 391 (2025), [135]

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, in which 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.

3.1. 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 near 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 [62]. 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 billion euros [13]. Recently, Spain and Germany announced that a CRM will be introduced [136, 137]. The EU used to consider CRMs as temporal measures, but now acknowledges that they may be needed permanently [138].

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 a SR because it is 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[139], system dynamics [140], and equilibrium models [30, 141]. 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 on the commissioning of investments as explained in Section 3.3.1. 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 [142].

Capacity mechanisms have been modeled with various ABMs. PowerACE was employed to model the German transition and the cross-border interaction [143]. EMIS-AS was applied to model the transition [144]. EMLab [145] was used to study strategic reserve and capacity markets. Nevertheless, those models model dispatch decisions with (linear) optimization problems while we apply another ABM for the short-term market, AMIRIS [57]. In AMIRIS, the dispatch is not based on a central objective function with perfect foresight, but rather based on the interplay of agents and robust storage dispatch strategies that cause an efficiency gap in comparison to an optimization approach [51, 146]. Through a co-simulation, we use the strengths of both models; EMLabpy (which is

[1] In case a Member State has resource adequacy concerns, the EU recommends implementing a strategic reserve [32], 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 [13]). Note, however, that buyers and sellers in CS meet in an exchange, similar to a central capacity market.

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 [147]. 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 that are optimized in the short-term rather than in the long-term [148, 149], 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 wrongly 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 to consumers' changing drastically their willingness to pay and a lack of long-term contracts.

The rest of the paper is organized as follows, Section 3.2 offers a synthesis of the current literature around implemented CRMs and offers an overview of the new CRM proposals for power systems with high share of VREs and high flexibility. Section 3.3 explains the applied co-simulation and how the strategic reserve, capacity market, and capacity subscription are modeled. Section 3.4 describes the data and the scenarios. Section 3.5 shows the results from the analysis, and their implications are discussed in Section 3.6. Finally, Section 3.8 concludes by summarising the paper's main findings.

3.2. 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 [15, 64]. However, this applies to a market under "ideal" conditions, such as with risk-neutral actors, perfect foresight, perfect competition, complete markets, etc. [27]. 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 [150].

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 [27]. 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 [20]. Additional factors contributing to the illiquidity of long-term markets, as identified by Batlle et al. [41], include the absence of demand response and policy interventions during periods of stress, among others. Ren et al. [151], 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 the missing market. In what follows, we subsequently discuss different capacity remuneration mechanisms (CRMs), differentiating between those that have been implemented (Section 3.2.1) and those that have been proposed for power systems with high shares of weather-dependent generation (Section 3.2.2).

3.2.1. 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 [152].

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 [154].

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" [152]. 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 [155]. 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 [156].

Although the European electricity regulation stipulates that CRMs should be technology-neutral [32], 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 [33, 154, 157]). 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

[3] It is typically sloped to prevent market power and to create some elasticity [30, 153]

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 [40]. Lynch et al. [50] 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[158]. 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. [159]. Reliability options (RO) can be used in centralized capacity markets to provide revenue clawback during periods of high wholesale market prices [160, 161].

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.

3.2.2. 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 their preferences [31]. In contrast, 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, 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 the last years, there have been more proposals to achieve resource adequacy through long-term energy products (paying for energy instead of capacity). For example, Wolak [20] 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. [41] proposed that suppliers should ensure a level of hedging. Furthermore, Bilimoria et al. [31]

proposed a mechanism in which consumers with a high VOLL pay for insurance for not 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 [162]. Note that CRMs and improvements of 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 [163]. 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 in which DSR should be available. More relevant is that DSR does not have a schedule obligation and can offer their capacity at a high declared price [157]. Lambin [164] argues that DSR that have very high activation prices (at VOLL or higher) and therefore get very seldomly activated (especially if there is already a lot of DSR enrolled) 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.

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 averaged VOLL, as it is done with current capacity markets [152], but through a decentral 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 [71, 166]. 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 [167].

In times of scarcity, the load-limiting devices restrict consumption to the subscribed

[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[165].

capacity levels. It may be a challenge for household consumers to select the level of capacity to which they subscribe. Options are to base it on their previous year's needs and require 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 [168] and Hu et al. [169]. 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 [170].

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 [157, 171]. 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 a 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 [172].

3.3. Methodology

We simulate a fully decarbonized power system and study the performance of an EOM, a 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 [57]. 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 3.4.1). 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 study (see Section 3.4) 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.

3.3.1. WORKFLOW

Figure 3.1 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 that are unprofitable (see 3.3.1). 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 3.3.1). As a last step, the capacity payments are computed, considering the CRM design at hand.

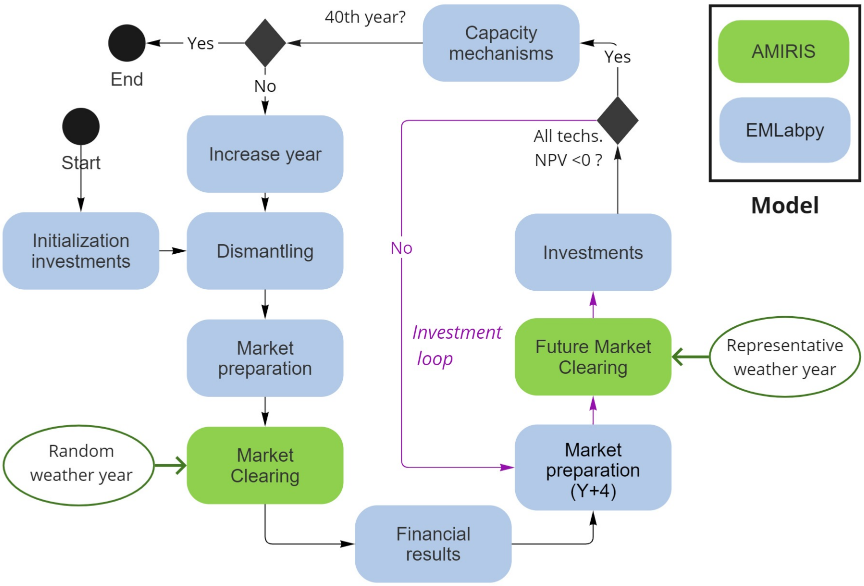


Figure 3.1: Overview of the co-simulation methodology.

[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, 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.

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 price with a margin. This forecast is based on the bids of inflexible agents and VREs availability. See Section 3.4.1 for a further description of the flexible load representation and [57] for more details about AMIRIS.

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 3.4).

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 plans, 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 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.

[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

3.3.2. POLICY OPTIONS

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

CAPACITY MARKET

Our model of the central capacity market is inspired by the Belgian CM [173]. The capacity demand curve's parameters (Fig. 3.2) 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 derating factor as explained in Art. 15 of the ACER methodology[152]. 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.

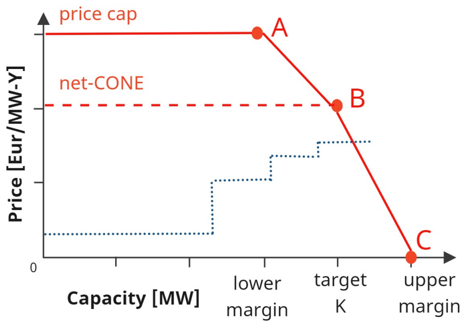


Figure 3.2: Sloped demand curve in our simulations considering a centralized capacity market.

For the supply side of the CM, we assume that companies bid their missing revenues, i.e., the additional revenues they would need to have 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]

$$\pi_y^{NewPlants} = \sum_{h \in H} p_h \cdot q_h - OPEX_y - FC_y - L_y \qquad \forall y \in Y \tag{3.1}$$

[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.

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

$$\pi_y^{ExistingPlants} = \sum_{h \in H} p_h \cdot q_h - OPEX_y - FC_y \qquad \forall y \in Y \tag{3.2}$$

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

$$bid_y = \max(0, \frac{-\pi_y}{K \cdot DF}) \qquad \forall y \in Y \tag{3.3}$$

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.

STRATEGIC RESERVE (SR)

In a 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 that is produced by a strategic reserve that is dispatched during a shortage must be at least equal to the VOLL [32]. [12] The SR operator (typically, the TSO) retains the market revenues and uses them to offset the cost of contracting the reserve capacity:

$$\pi_y^{SR\,Operator} = \sum_{t \in T^{SR}} \sum_{g} p_t \cdot q_{t,g} - SR_{y,g}^{payments} \qquad \forall y \in Y \qquad \forall g \in G^{SR} \tag{3.4}$$

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

$$SR_{y,g}^{payments} = \sum_{t \in T^{SR}} (OPEX_g \cdot q_{y,t,g}) + FC_{y,g} + L_{y,g} \qquad \forall y \in Y \qquad \forall g \in G^{SR} \tag{3.5}$$

In our simulation, plants are eligible to enter the reserve from 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 after they are no longer contracted. The technologies that may participate in a SR in our model are H_2 turbines and biofuel plants (see Section 3.4). Partial capacities are not accepted; therefore, an additional marginal amount of capacity may be contracted if required.

[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.

Because the SR is contracted one year ahead, the investment algorithm does not have information about which plants will be in the reserve in the investment reference year four 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.

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 [170]. 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 experienced shortages of the current simulation year and the total share of subscribed consumers. The consumers' bid prices and volumes for capacity are based on their differentiated VOLL (see table 3.1) and the duration and depth of the shortage (from the dispatch results of the current year). 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 $D_{CG,h}^{unsubscribed}$ by subtracting the subscribed capacity $K_{CG}^{subscribed}$ from their hourly demand $D_{CG,h}$. This represents the hourly load of each consumer group that can be limited.

$$D_{CG,h}^{unsubscribed} = max(0, D_{CG,h} - K_{CG}^{subscribed}) \tag{3.6}$$

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:

$$P(LL)_{CG,h} = \frac{D_{CG,h}^{unsubscribed}}{\sum_{CG} D_{CG,h}^{unsubscribed}} \tag{3.7}$$

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:

$$ENS_{CG,h} = P(LL)_{CG,h} \cdot ENS_h \tag{3.8}$$

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

$$bidP_{CG,0} = \sum_h min(1, ENS_{CG,h}) \cdot VOLL_{CG} \tag{3.9}$$

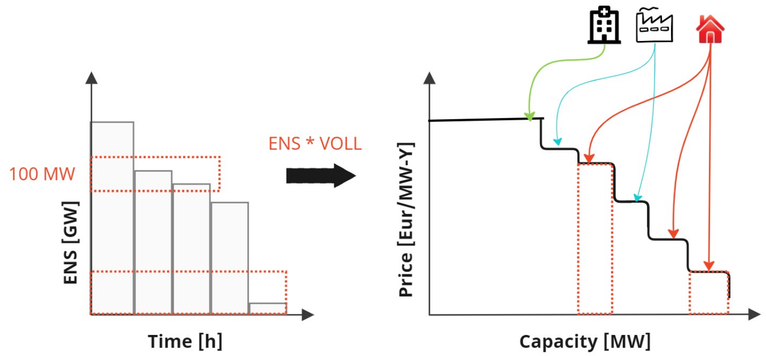


Figure 3.3: For each consumer group, the hourly energy not supplied, per blocks of 100 MW, determines the volume-price bids. In this way, we simulate consumer groups assigning different value to parts of their load. For example, households might value lower their EV load. The demand curve is then the aggregation of all consumers segmented bids.

This yields the bid price for $bidP_{CG,0}$ for the current subscription volume in the next capacity contract auction. Then, we determine the bid price $bidP_{CG,b}$ 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:

$$bidP_{CG,b} = \sum_{h} min(max(0, ENS_{CG,h} - (b-1)\cdot 100), b\cdot 100)\cdot VOLL_{CG} \tag{3.10}$$

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 $bidP_{CG,0}$. 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 3.3.2. 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.

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

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

3.4. 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 to assess the performance of the policy options.

3.4.1. DATA

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 ratio of 2 and 4 hours, photovoltaic (PV) systems, and biofuel. Based on [174], we consider H_2-fueled turbines. However, other options, like turbines fueled by synfuels, biogas, etc., would perform similarly [144]. 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 [175] (see Annexes 3.9 and 3.11).

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 [62].

INITIAL POWER PLANT PORTFOLIO

We take the initial power plant set from the output of the optimization model COMPETES [139], 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 3.9. We assume that one existing nuclear plant, Borssele (with a capacity of 484 MW), will remain operational rather than being decommissioned in 2033.

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 6,155 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 [176]. We augment historical demand profiles with the projected amount of HPs and account for the correlation with temperature (see [62]).

We consider the average of two studies of the Value of Lost Load (VOLL) of consumers in NL. See table 3.1. We assume that in the future, 11% of consumers, the ones with the lowest VOLL (household feed-in areas and industry SME) will be able to offer DSR, meaning they will have a VOLL of 1,500 Eur/MWh, which is lower than the power exchange price cap. In this publication, we refer to this load as DSR.

Table 3.1: The VOLL of different categories of consumers [177, 178]

	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 [177] 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. [178] determined VOLLs per consumer group through a production function approach. We applied a factor of 1.5 to account for inflation.

3.4.2. 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 with each mechanism, we compared one scenario of each mechanism, which are denoted in bold letters in the following tables 3.2, 3.3, and 3.4. To make the CRMs comparable, we sized them so that the involuntary load shedding was reduced at a similar level. [14]

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 3.2) with a scenario in which BESS and VRES also may participate ('CM_VRES_BESS'), following the recommendation in EU regulation Art. 22 of [32] about technology-neutral CRMs. We calculated the target capacity from the average peak load during the top 4 hours of scarcity in an EOM simulation of 40 weather years. For the CM scenario, the target capacity 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

[14] In practice, the SR will likely be sized to ensure that older power plants—which would otherwise be retired—remain operational. As a result, the required size of the SR could be smaller. This footnote was added after publication of the article.

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 based on the outcome of a market simulation for Y+4 considering a median weather year (see Section 3.3.2). 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. [15] Table 3.2 presents an overview of the CM scenarios.

Table 3.2: 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

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 at 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 [32]. 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.

We conduct a sensitivity analysis in which there is no DSR at a lower price than VOLL (SR_noDSR). In a SR, only H_2 turbines and biofuel are allowed to enter the reserve. The table 3.3 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.

Table 3.3: 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

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 from 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 [36].

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

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

(as explained in Sec 3.3.2) 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 3.4.

Table 3.4: 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

3.4.3. 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 3.4.1), and involuntary shedding, to which we refer as load shedding (LS).
  - Loss Of Load Expectation (LOLE) (hours/year): number of hours in which resources are insufficient to meet the demand. [16]
  - Hydrogen production (MWh): Power consumed by electrolyzers to produce hydrogen.
- Financial KPIs:
  - Weighted averaged yearly electricity prices (Eur/MWh):

$$\overline{p_y} = \frac{\sum_h^H p_h \cdot q_h}{\sum_h^H q_h} \tag{3.11}$$

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

$$C_y^{CRM} = p_y^{CRM} \cdot q_{y,g} \qquad \forall g \in G^{CRM} \tag{3.12}$$

  - Cost recovery (%):

$$CR_y = \frac{p_y \cdot q_y + C_y^{CRM}}{\sum_g (OPEX_y + FC_y + L_y + DP_y)} \qquad \forall g \in G \tag{3.13}$$

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

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

$$L_y = \frac{CAPEX \cdot D/E}{\frac{1}{i}(1 - \frac{1}{(1+i)^{T_{\mathrm{EL}}}})} \tag{3.14}$$

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

$$DP_y = \frac{CAPEX \cdot (1 - D/E)}{T_C} \tag{3.15}$$

– Weighted average CRM Costs (Eur/MWh):

$$\overline{p_y^{CRM}} = \frac{C_y^{CRM}}{\sum_h^H q_h} \tag{3.16}$$

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

$$C_y^{consumers} = \overline{p_y} + \overline{p_y^{CRM}} \tag{3.17}$$

– Total system costs (Eur):

$$C_y^{society} = \sum_g (VC_y + FC_y + L_y + DP_y) + ENS_y \cdot \overline{VOLL} \qquad \forall g \in G \tag{3.18}$$

The total system costs represent the total cost of generation plus the cost to consumers of any unserved energy. Here, the $\overline{VOLL}$ is the weighted average VOLL over all consumer groups in Table 3.1. For CS, $\overline{VOLL}$ is the weighted average VOLL of unsubscribed demand sections.

– Normalized annual NPV (Eur):

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

$$CashFlow_y = \begin{cases} -DP_y & \text{for} \quad 0 \geq y \geq T_C \\ p_y \cdot q_y + C_y^{CRM} - FC_y - VC_y - L_y & \text{for} \quad T_C > y \geq T_C + T_{EL} \end{cases} \tag{3.19}$$

The debt interest rate ρ was the same for all technologies

$$NPV_y = \sum \frac{CashFlow_y}{(1+\rho)^y} \tag{3.20}$$

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

$$nNPV_y = \frac{NPV_y}{K} \tag{3.21}$$

3.5. 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.

3.5.1. ENERGY-ONLY MARKET (REFERENCE CASE)

In the EOM simulation, the LOLE was above 4 hours for 26 years, 4.23 hours 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. Figure 3.4 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 strongly 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 3.3.1) and because we do not model ramping constraints on competing dispatchable technologies or ancillary services markets, reducing the profitability of BESS.

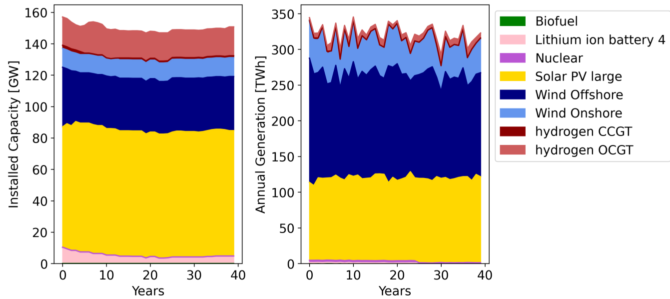


Figure 3.4: Left: Installed capacity per technology in an EOM. Solar energy was the technology with the highest installed capacity. Right: Annual generation per technology in EOM. The annual production of wind energy was volatile year-to-year.

3.5.2. 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 of H_2-OCGT (see Fig. 3.5). For the scenario where DFs were calculated ex-ante, the BESS with an E-P ratio of 4h resulted in a DF of 25%, and the ones of 2h 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 of 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 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.

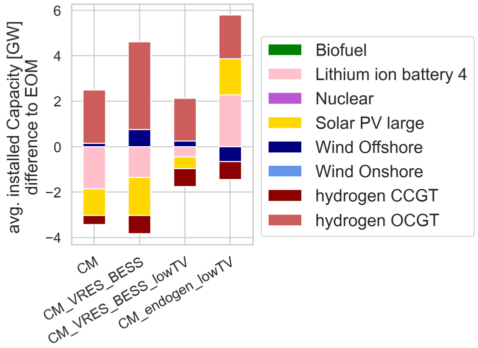


Figure 3.5: Difference in the average installed capacity over the last 10 simulation years between the CM scenarios and an EOM. In all CM scenarios, the installed capacity of H_2-turbines increased.

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 3.5). With a lower target volume, the shortages in the scenarios that awarded VRES and BESS were at a similar level as the CM where only dispatchable technologies participated. However, one year, there was a very high shortage of almost 100 GWh (higher than with an EOM), as shown in Fig. 3.6, illustrating the risk of estimating the DF of VREs and BESS based on average performance that may hide very poor performance in extreme years.

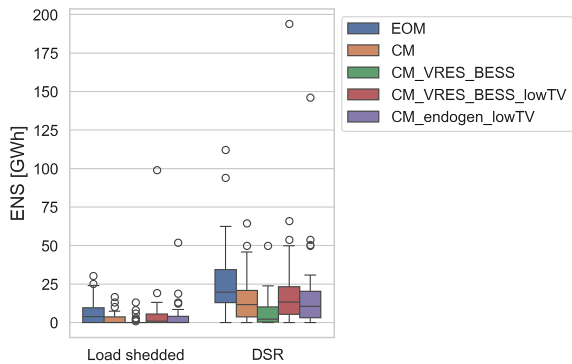


Figure 3.6: ENS was reduced in all CM scenarios. Allowing BESS and VREs to participate in a CM with a lower target volume led to high ENS volumes in years with low VREs.

Fig. 3.7 shows that CM prices were very volatile, which may be attributed to the my-

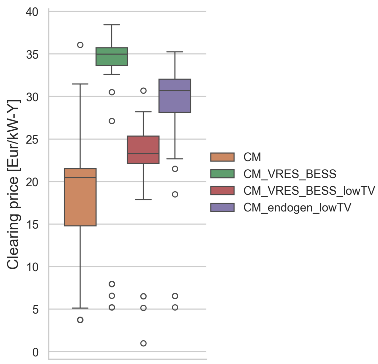


Figure 3.7: Capacity market prices were constantly higher if it was oversized.

opic 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. 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. 3.8. 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 3.5, 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.

3.5.3. 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 of H_2-OCGT and offshore investments, as shown in Fig. 3.9. 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. Figure 3.10 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 much higher costs

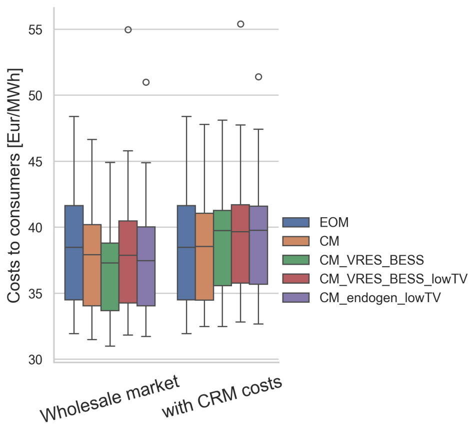


Figure 3.8: Capacity market reduced wholesale market prices but adding up the capacity costs, the yearly costs to consumers were higher than an EOM, except in CM scenario.

Table 3.5: 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	15797	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]	$\overline{x}$	10543	10302	10320	10539	10445
	σ	711	653	602	959	754
CRM costs [mln. Eur]	$\overline{x}$	0	321	721	484	610
	σ	0	188	361	219	265

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. 4.9b), 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. 3.12. 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 hours, and the LOLE increased from 2.3 to 10.85 h/Y. More volatile and higher electricity prices incentivized more batteries and solar energy, as shown in Fig. 3.9. Due to the fewer in-

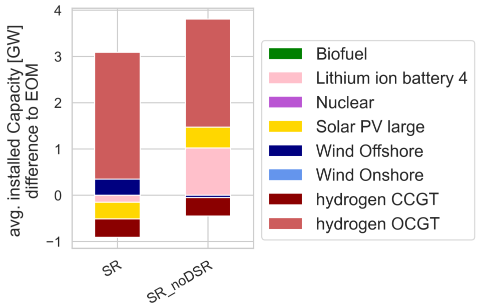


Figure 3.9: Average difference of installed capacity in 10 last simulation years with SR scenarios. Without DSR prices were more volatile which incentivized more batteries

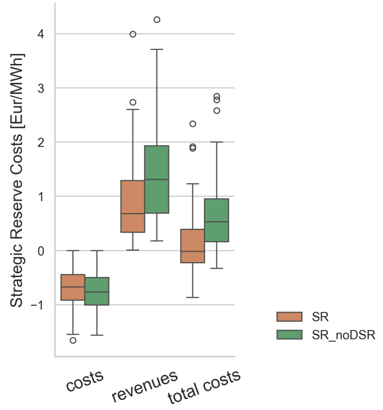


Figure 3.10: Adding up yearly costs and surplus revenues from power plants in the strategic reserve, the extra costs were almost 0 Eur/MWh.

voluntary shortages, the SR_noDSR scenario presented lower total system costs than a SR with DSR. However, that scenario presented the highest costs to consumers, as presented in Table 3.6. We also tested a 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.

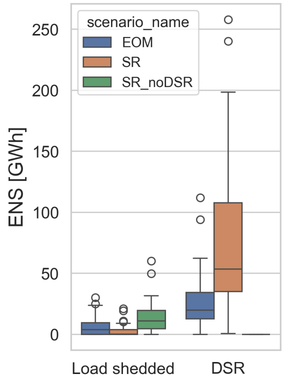


Figure 3.11: In a SR_noDSR the involuntary load shedded was higher because there was no DSR activation.

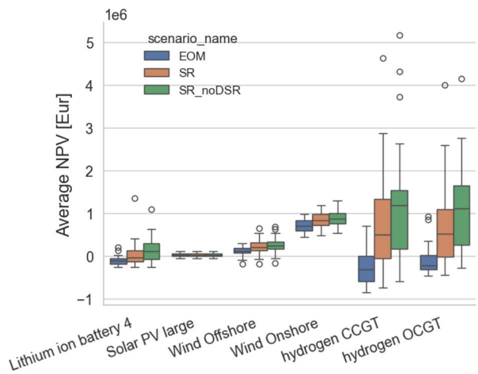


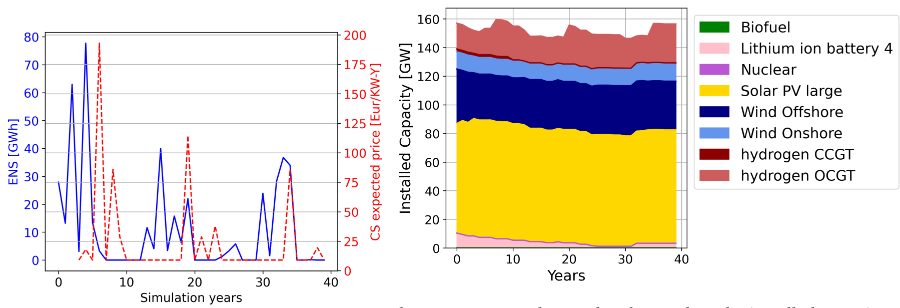
Figure 3.12: Annual normalized NPV by technology in SR scenarios

Table 3.6: SR results

		EOM	SR	SR_noDSR
ENS [MWh]	$\overline{x}$	6375	2992	8129
	σ	7577	5157	11103
LOLE [h]	$\overline{x}$	4.23	2.30	10.83
	σ	4.77	3.29	9.47
Weighted average	$\overline{x}$	38.53	42.92	46.60
electricity prices [Eur/MWh]	σ	4.47	8.02	8.53
Cost recovery [%]	$\overline{x}$	120.71	136.75	148.89
	σ	8.26	19.66	22.08
Weighted average	$\overline{x}$	0.00	0.74	0.78
CRM Costs [Eur/MWh]	σ	0.00	0.37	0.38
Cost to consumers	$\overline{x}$	38.53	42.96	46.17
[Eur/MWh]	σ	4.47	7.49	7.82
Total system costs	$\overline{x}$	10543	10466	10368
[mln. Eur]	σ	711	700	672
CRM costs	$\overline{x}$	0	235	249
[mln. Eur]	σ	0	112	115

3.5.4. RESULTS: CAPACITY SUBSCRIPTION

Capacity subscription led to investment cycles (see, e.g., the installed capacity of H_2-OCGT in Fig. 3.13b). 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 periods of low CS prices and, subsequently, a decrease in investments, resulting in more shortages. Figure 3.13a shows how, following years of shortages, the expected CS price peaks with a delay.



(a) ENS and expected CS price

(b) Investment cycles can be observed on the installed capacity of H_2-OCGT

Figure 3.13: 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.

The WTP increased substantially following years of severe shortages, resulting in extremely high CS prices. The CS prices, shown in Fig. 3.14 illustrate that the CS_noMemory was the scenario with the highest capacity price volatility, indicating 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. 3.15, and fewer shortages. However, as shown in Table 3.7, 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 to 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.

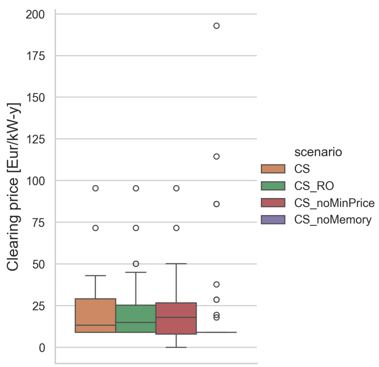


Figure 3.14: Yearly CS clearing price

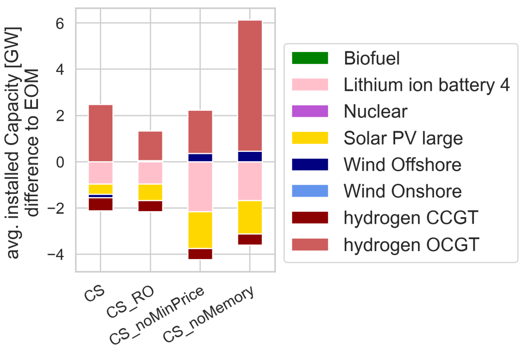


Figure 3.15: Difference in the average installed capacity in 10 last simulation years between the CS scenarios and an EOM

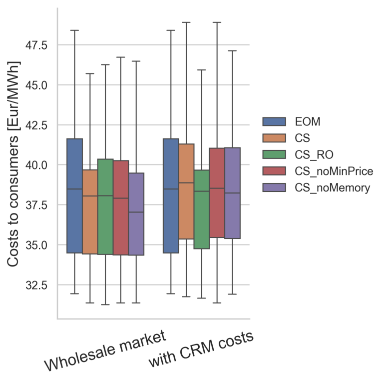


Figure 3.16: Yearly costs to Consumers in CS scenarios

If a clawback is implemented, the mechanism can provide price stability to subscribed consumers in a market-compatible manner[17]. A clawback reduced cost recovery for generators by 7%, see Table 3.7, and lowered the costs to consumers by 1 Eur/MWh, as shown in Fig. 3.16. Furthermore, it reduced the windfall profits of plants that had already recovered their fixed costs, and in some years, the returned clawback was higher than the CM costs (Fig. 3.17).

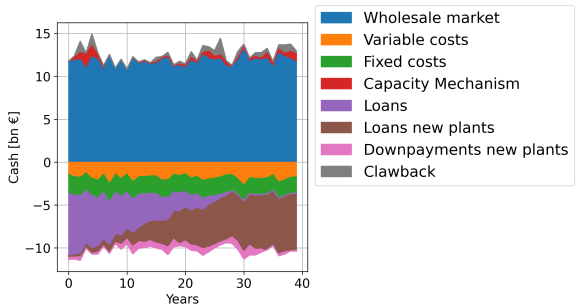


Figure 3.17: Cash flows in CS_RO scenario

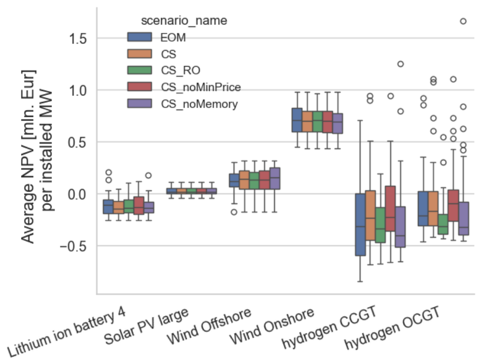


Figure 3.18: Annual normalized NPV by technology in CS scenarios

3.5.5. 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 a SR. Figure 3.19 shows that all CRMs accomplished the main goal of reducing shortages to a similar level. However, a SR caused higher DSR activation since the plants in reserve became active only after the DSR. As depicted in Fig. 3.20, the yearly installed capacity of dispatchable technologies was most stable with a CM. This was the reason for CM presenting the lowest shortages. Lower

[17] While CS promotes more dispatchable capacity, the original design doesn't shield consumers from high electricity prices [166]. Ensuring sufficient capacity does not translate into price protection for consumers because a shock in fuel prices or high-price imports can still occur.

3

Table 3.7: 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]	$\bar{x}$	10543	10458	10495	10464	10461
	σ	711	649	669	666	609
CRM costs [mln. Eur]	$\bar{x}$	0	406	-1	384	457
	σ	0	363	452	384	712

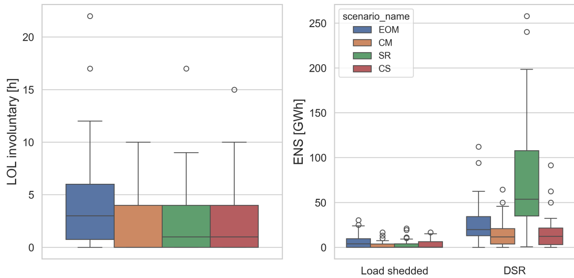


Figure 3.19: LOLE and ENS by CRM. The mechanisms reduced the shortages to a similar LOLE and ENS. However, the activation of the DSR was much higher in a SR.

voluntary and involuntary curtailment led to lower total system costs, which were the lowest with a CM (see Fig. 3.21). The lack of a long-term investment signal is an issue with CS and SR.

Fig. 3.21 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, a 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 of H_2-OCGT improved and became more stable, but the profitability of BESS decreased, which reduced their installed capacity as shown in Figs. 3.22 and 3.23.

Table 3.8 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 a 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 than an EOM, and this can be even lower if a clawback is implemented. In a SR, the volatile electricity prices can incentivize more

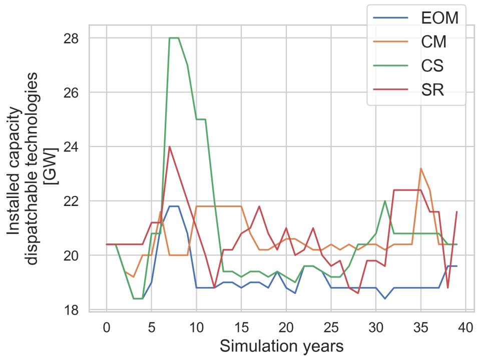


Figure 3.20: Yearly installed capacity of dispatchable technologies which include nuclear, bioenergy, and H_2 turbines

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.

Table 3.8: Qualitative comparison of CRMs

	EOM	CM	SR	CS
Limiting shortages	− −	+++	+ + [a]	++
Reducing total system costs	0	++	+	+
Reducing costs to consumers	0	−	− −	−
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

3.6. 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 possibil-

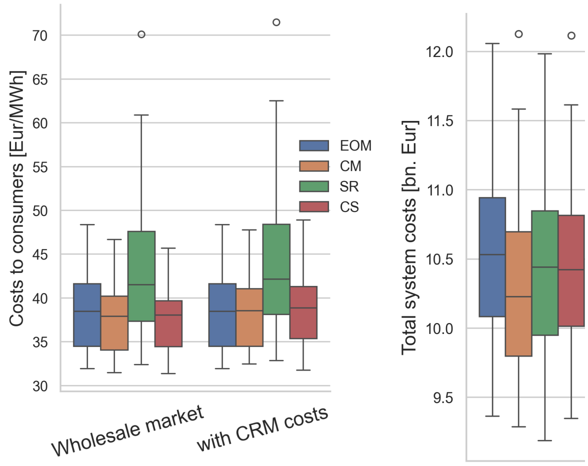


Figure 3.21: A CM was the mechanism that reduced total system costs without increasing the costs to consumers

ity of consumers underestimating the risk of scarcity events and the resulting investment cycles.

3.6.1. 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 [179]. Furthermore, we assumed that fuel prices would remain constant; however, fuel prices could increase fluctuations in the wholesale market revenues. [18] In many European markets, the CONE is set by DSR, which has very broad values ranging from 7,500 Eur/MW to 60,000 Eur/MW [13]. 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 increasing flexibility of demand. The net contribution of each technology depends, among others, on the weather, which makes estimating the derating factors (DF) a nearly impossible task and prone to self-fulfilling or self-destroying parametrization [155]. 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 a RO is implemented, as Mastropietro ex-

[18] 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.

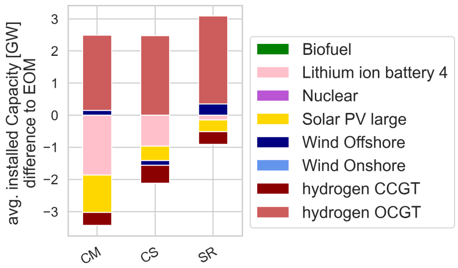


Figure 3.22: Difference in the average installed capacity over the last 10 simulation years between CRM scenarios and an EOM.

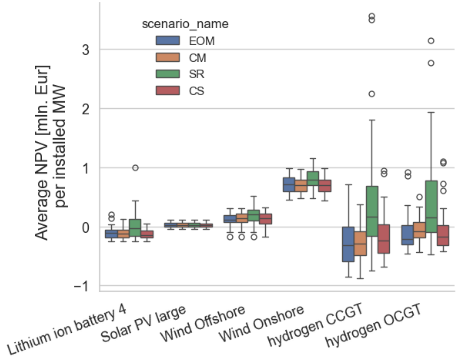


Figure 3.23: Normalized annual NPV by technology

plains that participating power plants would factor in the probability of incurring penalties for unavailability during scarcity periods [159]. 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 [180, 181].

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 [156]. Furthermore, battery operators may be exposed to high penalties if these are not available at scarcity moments [182]. Billimoria et al. suggest an alternative way to remunerate batteries through a revenue collar with a soft cap and a yardstick contract basis [183]. An overview of other options can be found in [184].

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.[19] Securing long-term capacity contracts could offer lower capital costs because the debt share could be higher and the equity returns could be lower [19, 185, 186]. An advantage of subsidizing capacity through auctions is the facilitation of a more coordinated deployment while creating competition.

3.6.2. 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) [79]. Demand flexibility and storage may set the electricity

[19] In reality, the majority of capacity market payments are awarded in long-term contracts [13].

price during scarcity moments.[20] 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 a 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 [187]. Moreover, when taking into account risk aversion, scarcity pricing methods are not as efficient as promoting the creation of extra capacity through a CM [140]. 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 [188]. For these reasons, a 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, a SR could prove advantageous, as identified by Holmberg [189]. Nevertheless, in the long term, this mechanism might not be the most suitable.

3.6.3. 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.

[20] 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.

In our simulations, the maximum load limited during scarcity hours was consistently lower than the volume 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.

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 [190].

In CS, there could also be multiple reliable levels, similar to priority pricing, where consumers receive differentiated electricity prices for different “reliability levels” of consumption [157]. 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 disproportionally 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 [151].

3.7. 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 [21], risk aversion, or penalties that may be imposed if generators that receive 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

[21] 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. [191]

consider fuel price, electricity demand growth, disruptive technology innovation, 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 in 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 [180]. 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, in the 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 [192], 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 in scarcity moments.

3.8. 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 a 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. A 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 that 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 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.

3.9. APPENDIX

Table 3.9: Technologies costs [175]

	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	7,893	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	7,400	0.50	-	-	-	-	25	82,099	107.9
Solar PV rooftop	640,000	8,900	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 3.10: Other technologies data

	Max. lifetime extension	Permit time	Lead time	Investment block	Debt interest rate 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 3.11: Fuel costs [175]

	Eur/MWh
Nuclear	1.69
Biofuel	50.29
Hydrogen	45.07
CO_2	168.00

4

Capacity Remuneration Mechanisms for Power Systems in Transition

This chapter is under revision and will be published as: I. Sanchez Jimenez, S. Johandeiter, and L. J. de Vries: "Capacity Remuneration Mechanisms for Power Systems in Transition"

4

Abstract

During the energy transition, investors will face increasing risks due to higher uncertainties regarding new technologies, electrification, and, most recently, an increasingly weather-dependent production. Over the past years, capacity remuneration mechanisms have been introduced in more European Member States and have evolved from temporary to permanent solutions to ensure resource adequacy. In this study, we analyze the effects of introducing a strategic reserve, a capacity market, and capacity subscription, as well as their interactions with different CO_2 limits on eligible technologies during the transition of a power system based in the Netherlands. We apply a co-simulation of two agent-based models. We find that a strategic reserve can effectively reduce shortages during the energy transition, but at the cost of high and volatile wholesale prices. As an alternative, capacity subscription can incentivize demand-side response from all consumers; however, it requires guidance to prevent investment cycles. Furthermore, we found that weather can have a higher impact on CO_2 emissions than the market design. However, we recommend carefully implementing CO_2 limits on eligible technologies for CRMs to ensure their effectiveness.

4.1. INTRODUCTION

We study the performance of capacity mechanisms in the electricity market in providing sufficient investment in dispatchable electricity generation capacity during the energy transition. The novelty of this research is that it studies their effectiveness in supporting the transition from a partly fossil-based generation mix to a carbon-free system.

There is a long-standing debate among energy economists about whether electricity markets can guarantee resource adequacy. One argument for intervention in the form of a capacity mechanism is that the key assumption of the electricity spot pricing theory [193, 194] does not hold in practice [195, 196]. A price cap may cause the missing money problem, while insufficient price-elastic demand may also cause market failure. Additional challenges arise from uncertainties regarding future electricity market developments, such as regulatory interventions, price volatility, structural changes in demand, and technological advancements. In addition, random consumer curtailments in case of outages discourage consumers and their retailers from hedging sufficient capacity. During the transition to a decarbonized power system, these uncertainties are increased, posing a challenge for risk-averse market actors who face a lack of long-term contracts, known as the missing market problem [19].

4

Capacity remuneration mechanisms (CRMs) are policy instruments that are designed to alleviate the missing money and missing market problems and to compensate for other market shortcomings, such as risk aversion of investors, by providing revenues to dispatchable power plants for being available in addition to spot market revenues [197]. Since 2020, the number of European countries that plan to introduce or have implemented CRMs has more than doubled [13]. This research investigates the suitability of different types of CRMs in agent-based model of the future Dutch power system in transition from 2020-2050.

Previous work on CRMs in the energy transition is typically based on optimization models with perfect foresight, equilibrium analyses, and/or single-year snapshots. These studies tend to neglect the uncertainties that exist during the transition phase and do not reflect the fact that the electricity sector will not be in a long-term (investment) equilibrium for the foreseeable future. For this reason, we test the performance of CRMs during the energy transition with an agent-based model in which investment decisions are made in an iterative manner without full knowledge of the future, transitioning from the current generation mix to a carbon-free end state. Simulating yearly rolling-time horizon investment decisions allows us to derive insights into investment dynamics.

We conducted a co-simulation of two models to combine their strengths: we used the model AMIRIS [57] to simulate hourly electricity dispatch and EMLabpy, which is derived from EMLab [145], to simulate investment decisions. This model combination was first described in [62]; this study is its application to transition pathways. We enhance the analysis by analyzing a transition scenario with increasing demand and increasing flexibility sources (see Section 4.3). We consider weather stochasticity, simulating that the realized weather is based on historical weather years. We evaluate a capacity market (CM), a strategic reserve (SR), and capacity subscription (CS), each with three different CO_2 emission limits. Comparing the results with respect to resource system costs, we find that for the transition, SR reduced the total system costs, however, through high volatile prices.

The remainder of this research is organized as follows: Section 4.2 provides a literature review on capacity remuneration mechanisms. Section 4.3 describes the co-simulation, and Section 4.4 presents a case study based on the Netherlands. Section 4.5 discusses the results, and Section 4.7 concludes.

4.2. Literature Review

In this section, we first review the literature on uncertainties that arise during the transition to a decarbonized power system. Second, we use the literature to classify types of CRMs and their current implementation status in Europe. Third, we review previous evaluations of the effectiveness of CRMs in the energy transition and the incorporation of CO_2 limits in CRMs.

4

4.2.1. Additional investment risk during the energy transition

With the announcement of its Green Deal, the European Union pledged to become the world's first climate-neutral economy by 2050 [198]. This implies that the electricity supply will increasingly be driven by solar and wind power plants (cf. [199] and [200]). When solar and wind power are available, they decrease electricity prices by shifting the electricity supply curve to the right, known as the merit-order effect [201]. In current markets with low flexibility, this poses additional risk to investments in dispatchable power plants [202]. For highly renewable power systems, Sanchez Jimenez et al. [62] show that investors in dispatchable power plants are exposed to significant price fluctuations and high annual variations of their full load hours.

The intended decarbonization of transport, industry, buildings, and fuel production causes significant uncertainties regarding these sector's degree of direct electrification. For example, a recent study in the USA projects a wide range of possible electricity demand growth rates for 2050, i.e. from 150% to 280% from 2020 levels [203]. Likewise, the European Commission's long-term strategic vision of a "Clean Planet for All" [204] provides different scenarios of Europe's 2050 level and composition of final energy consumption ranging from approximately 610 Mtoe to 810 Mtoe with electricity shares varying between 42 and 55%. Additional uncertainties exist regarding developments on the demand side, such as energy efficiency, electrolytic hydrogen demand, and data centers, and on the supply side, such as small modular nuclear reactors.

Further challenges for investors arise from regulatory uncertainty, such as revenue caps implemented during the energy crisis in 2022 [205], changing policies regarding the phase-out of fossil power plants, and the growth rate of renewable energy. In Germany, for instance, a commission of different affected stakeholders agreed to phase out coal by 2038 after a lengthy decision process that ended in 2019 [206]. Yet, this coal exit date was moved forward to 2030 by the government that took office in 2021 [207].

In an energy-only-market (EOM), forward and futures markets are the standard instruments for derisking the necessary investments to achieve decarbonization targets [208–210]. However, European forward market liquidity remains limited. Therefore, in light of the energy crisis, ACER [211] and scholars proposed the introduction of instruments to increase forward market liquidity, such as market maker obligations [70]. Fabra [68] argued for the necessity of governmentally issued long-term contracts.

4.2.2. CAPACITY REMUNERATION MECHANISMS

Capacity remuneration mechanisms (CRMs) complement an EOM by rewarding generators for their availability during scarcity events. The latest amendment to the European regulation (EU) 2019/943 [138] no longer considers CRMs as a temporary or last resort measure but as a structural part of the market design. The regulation postulates a strategic reserve (SR) as the first mechanism of choice. An SR consists of several power plants that are taken out of the market to serve as backup capacity [197] that – according to the EU regulation's Article 22 – shall be dispatched only if the transmission system operator's balancing resources are likely to be exhausted. Furthermore, it prescribes a settlement price at the level of the market price cap or the value of lost load (VOLL) [212]. Holmberg & Tangerås [213] argue that SRs are particularly suitable for highly renewable power systems, as they merely require the definition of the required firm capacity. As of 2022, in Europe, SRs are implemented in Sweden, Finland, and Germany [13].

Several countries around the world have implemented capacity markets (CM). In a CM, a central authority sets a demand curve for generation capacity and purchases capacity contracts from generators through an auction [153]. The system operator usually adjusts the offered generation capacity according to derating factors that reflect each technology's statistically expected contribution to reliability [214]. According to Neuhoff et al., [215], CMs potentially decrease the market's liquidity for long-term contracts and cause distortions in spot market prices that are particularly important to incentivize flexibility. Another criticism is the limited demand-side response (DSR) participation in CMs. A report from ACER [13] explains DSR's relatively low participation in Europe with minimum capacity and strict availability requirements. Furthermore, most CRMs require participating technologies to be available all year round. Long-time leads between the contract and the delivery time, may also hinder the participation of DSR.

The contribution of DSR to resource adequacy can be improved by a not yet implemented mechanism called capacity subscription (CS). With CS, individual consumers contract the capacity they consider indispensable during scarcity events. Such an arrangement incentivizes them to reduce demand in scarcity times [170]. In Europe, the closest real-life implementation to CS is the French decentralized capacity market, where suppliers are obliged to procure capacity guarantees that reflect their customers' electricity consumption during peak load periods [214]. In contrast to CS, which is based on single-year contracts that are auctioned annually and where DSR participates implicitly through its demand for firm capacity, in the French capacity market, DSR can participate both implicitly and explicitly and in several auctions. However, the French experience faced several issues. Although the mechanism was designed to incentivize more flexibility, the implicit DSR participation remained at the very low level of 300 MW. Furthermore, the control of small loads turned out to be more complex than expected. In the French CM, players can exchange certificates over the counter or in the auctions from Y-4 to Y+1. This has allowed a large part of the demand (5 GW) not to be covered in the year prior to the delivery year, and several suppliers deferred their expenses to billing periods, leading to a fragmentation of the price formation. On the supply side, the offered volumes remained limited. Therefore, capacity prices were highly volatile [216]. In conclusion, these short lead and contract times may not suffice to incentivize sufficient investments [136]. Recently, France decided to switch to a central CM. The German government is currently considering the introduction of a combined capacity market, which joins the strengths of a central and decentralized CM [207] (see more in Section ??).

4.2.3. The performance of CRMs in the energy transition

Several studies use different modeling approaches to evaluate CRMs in power systems with increasing renewable shares. Optimization models typically assess CRMs by implementing a constraint that enforces installed firm capacity to exceed a margin on peak load [217]. A CM decreases the occurrence of scarcity prices and the profitability of VRES and baseload capacities, as compared to an EOM, particularly with increasing shares of renewables [218]. Similarly, in a greenfield optimization model with renewable premiums, CMs are found to depress energy prices compared to an SR scenario, leading to higher required premiums for renewables [219]. Another study finds that with a CM, the profitability of energy storage is worsened due to derating factors while those of thermal power plants improve [220]. Furthermore, DSR can potentially reduce energy prices and capacity payments in a CM, particularly at high levels of wind generation [50]. In a brownfield model, however, the price effects of CMs are found to depend on the countries' merit order curves which change over time[221].

All of the above-cited studies assume perfect foresight and equilibrium investment based on single-year snapshots, failing to capture dynamic effects such as investment cycles. While optimization models can be used to model transition pathways, investment expansions over long time horizons are often based on representative time steps to remain computationally tractable [222, 223]. In highly renewable power systems, such sampling methods may result in significant deviations from investment decisions based on the complete time horizon [98].

Agent-based models can reflect the myopia of real investors' decisions by basing the investment decisions on the expected net present values (NPVs) at the time of investment and given realistic information about the future, and without assuming equilibrium. Khan et al. [110] concluded that storage and DSR might reduce the need for a CM and recommended the participation of storage in CMs. Similarly, Fraunholz et al. [143] recommend allowing batteries in CRMs but also acknowledge the complexity of estimating their derating factor. However, they implemented an exogenous derating factor and exogenous renewable energy expansion. Hary et al. [224] presents a model that reflects investment decisions in all technologies but does not focus on decarbonization challenges. They find CMs to be more efficient than SRs in reducing outages. Bhagwat et al found that a CM is more efficient than an SR in a market with a growing share of renewables in the presence of imperfect information and uncertainties, as an SR may not dampen investment cycles sufficiently. [25] In a previous study [135], we found that in a decarbonized power system, in comparison to an SR and CS, a CM was the mechanism that reduced the shortages the most, presenting the lowest total system costs and higher price stability. In this research, we modify the model that was used in that study to represent the pathway to decarbonization in the Netherlands.

4.2.4. Capacity remuneration mechanisms and CO_2 emissions limit

CRMs are designed to support dispatchable plants, and fossil-fueled plants tend to benefit. With the Clean Energy Package reform of 2019, the EU established a limit on CO_2

emissions from generators that receive CRM payments of 550 g of CO_2 per kWh [212][1]. However, many member states have not implemented these changes. From 2019 to 2022, the share of fossil-fueled power plants in European CRMs increased from 34% to 46% [13]. For instance, in Poland, coal power plants have received the majority of capacity payments in recent years, thereby delaying the decarbonization of the power system. [225, 226]. In contrast, some member states, such as Belgium, are already considering gradually lowering the CO_2 emission limit [227]. To the best of our knowledge, there exists no model-based evaluation of the role of CO_2-limits in CRMs.

4.3. METHODOLOGY

To analyze the transition to a future Dutch power system, we apply a co-simulation of an agent-based dispatch model of the spot market and an agent-based power plant investment model. Particularly, we apply the co-simulation of the ABMs, EMLabpy and AMIRIS, as developed in Sanchez Jimenez et al. [62]. In EMlabpy, investment decisions are based on the expected net present value (NPV) of four years ahead (Y+4) market dispatch simulated by AMIRIS and capacity remunerations from the mechanisms described in Sanchez-Jimenez et al. [135]. The investment cycle begins with investing in the technologies with the highest expected NPV and stops as soon as the expected NPV of further investments drops below zero[2]. In AMIRIS, dispatch decisions are modeled with an hourly resolution and a robust battery dispatch strategy [51, 62].

The study of transition pathways between 2020 and 2050 required some modifications to the model. Similar to our previous study, the investment algorithm is based on simplified NPVs derived from the revenues and amortized annual costs projected for four years into the future (Y+4), corresponding to the first year of operation. For CO_2 prices, however, we extended the investors' look-ahead period from 4 to 14 years because the CO_2 cap declines and gas turbines rapidly become unprofitable if the CO_2 prices increase. In contrast to other fuel price developments, the direction of the CO_2 price trend is assumed to be more certain.

Compared to the previous study, we raise the fixed costs of power plant lifetime extensions to 5% per year. This assumption is relevant since we do not simulate early retirement; plants can only be decommissioned after reaching their technical lifetime. A plant's lifetime can be extended (up to a maximum per technology as specified in Table 4.5) if its net profit has been positive in the past years.

We model a capacity market (CM), a strategic reserve (SR), and capacity subscription (CS) and compare their performance with an energy-only-market (EOM) reference case. In line with EU regulations (cf. Section 4.2.4), we implement different CO_2 emission limits for power plants eligible for a CRM. In the following, we briefly describe the main elements of the modeled CRMs, while more details can be found in our previous publication [135].

[1] For generation capacity that started production on or after 2019, an emission limit of 550 gr CO_2 of fossil fuel origin per kWh of electricity and 350 kg CO_2 of fossil fuel origin on average per year per installed kW applies.

[2] Similar to our previous study, new investments enter the market with a four-year delay regardless of the technology. Otherwise, the shorter time lead of some technologies could have resulted in investment cycles.

4.3.1. Capacity Market

We model a CM as a pay-as-cleared auction, where a central authority procures a target demand for firm capacity. The target demand is set endogenously as the average of the inflexible demand during scarcity and near-scarcity hours (i.e. when demand-side response (DSR) is activated, see Section 4.4), based on the EOM results projected three years in advance.[3]. The inflexible demand includes the heat pumps demand, which is dependent on the realized temperature. For this reason, the realized demand differs from the system operators' prediction.

On the supply side of the CM, power plants offer firm capacity at their missing money, which refers to the additional revenues required to achieve a positive NPV in the subsequent year. If this value is below zero, then they behave as price takers and bid 0 in the CM. The CM auction is cleared 4 years ahead of the construction of new power plants. On the upper end, the price cap of the auction is set (once, at the beginning of the simulations) to the cost of new entry (CONE) of the least expensive new entrant technology.

We consider different scenarios of eligible technologies for the CM (cf. 4.4.5). If VREs and BESS are accepted as suppliers of capacity, these technologies are derated by an endogenously calculated derating factor (DF). The calculation is based on the availability of these technologies during a future dispatch simulation (Y+4) of scarcity and near-scarcity hours. As the resulting DFs can be very volatile, we take the average of the past 4 years. We deduct from target demand the capacities of active power plants whose CO_2 emissions exceed the CO_2 limit of the CM (cf. 4.4.5) and thus are ineligible to participate in the CM. Similarly, we deduct the capacity of other technologies that don't participate in the CM, according to the scenario, yet contribute to adequacy.

4.3.2. Strategic Reserve

We model SR with a capacity of 15% of the residual peak load of a median weather year. The plants in the SR are removed from the spot market but remain available to be dispatched during moments of scarcity by an SR operator. The power plants with the highest operating costs are contracted for the SR one year ahead. They remain in the reserve until their maximum lifetime extension is reached. Following the EU regulation [212] (as explained in Section 4.2), the dispatch of power plants in the SR is settled at the spot market model's price cap of 4000 Eur/MWh. The revenues are retained by the SR operator who, in turn, pays for the fixed and operating costs of the plants in the reserve. The market parties base their investment decisions on the assumption that the plants that are currently in the reserve will remain there. In contrast to the previous implementation of this model, where power plants were only eligible for the SR when they were close to the end of their lifetimes, generators in this study can qualify for the reserve from their first years of operation. Otherwise, there could be many years of insufficient capacity in the reserve. In contrast to the CM scenarios, we do not consider the possibility of lithium-ion batteries participating in the SR. This is because these plants generate substantial revenues from ancillary markets, and their participation in the reserve would eliminate this income stream.

[3] This is similar to the Belgian CM in which the auction volume is calculated with the average load during scarcity hours in an EOM minus a remaining LOLE.

4.3.3. CAPACITY SUBSCRIPTION

CS is modeled as a decentralized capacity market, in which consumers procure their desired level of firm capacity for the upcoming year in a pay-as-cleared auction. During electricity supply shortages, individual consumption is limited to the procured capacity. We consider different consumer groups, whose aggregated demand for firm capacity is a decreasing step function of their willingness to pay (WTP) during periods of scarcity. The initial WTP of each consumer group is determined by different values of lost load (VOLL; based on [177, 178]). The WTP is adjusted yearly according to the probability of curtailment, based on the length and depth of past shortages and the total share of subscribed consumers. Power plants offer their capacity on the supply side, just like in the CM, i.e., for a price that represents their missing money. Since the CS auction takes place one year before the investment decision, investors estimate the future CS price based on the CS price average over the past three years.

4

4.4. CASE STUDY: THE ENERGY TRANSITION IN THE NETHERLANDS

We apply the co-simulated models to a case study of the Dutch power system in transition from 2020 to 2050. Input data assumptions for 2050 are the same as in our previous studies [62, 135]. We will now explain the additional assumptions made for this transition study.

4.4.1. THE INITIAL POWER PLANT PORTFOLIO

The initial power plant capacities are obtained from aggregated data from [228]. We enforce the decommissioning of coal power plants by 2030, as is public policy in the Netherlands. Our model does not simulate cross-border transmission; for this reason, the simulated capacity is higher than the actual installed capacity. As a consequence, the results do not accurately resemble the energy transition of the Netherlands, but the focus of this study is on the relative performance of CRMs, not on forecasting market developments.

4.4.2. GENERATION TECHNOLOGIES

Available technologies for investment are PV, wind onshore, wind offshore, bioenergy, lithium-ion batteries (with an energy-to-power ratio of 4, and denoted as lithium-ion batteries 4), nuclear, hydrogen open-cycle gas turbines (H_2 OCGT), hydrogen combined cycle gas turbines (H_2 CCGT), natural gas (NG)-CCGT, and NG-OCGT. Technology costs are linearly interpolated from 2020 to 2050 and were taken from the database of the European research project TradeRES, of which this study was a part [175]. (See Annex 4.4.)

4.4.3. VRES PROFILES AND LOAD REPRESENTATION

We use the weather sequence from 1980 to 2010 to represent the years 2020 to 2050 in our dispatch simulations from [98]. We simulate a linear demand increase from 2020 to 2050 according to the time series of the TYNDP global ambition scenario from ENTSO-E[119]. The demand from electric vehicles (EVs) is scaled to the 2050 projected fleet size, and the time series is based on the Charging Profiles of Electric Vehicles Model [120]. The heat pumps' (HP) demand is simulated according to the number of installed heat pumps and correlated with the hourly temperature, as explained in [62]. For the investment decisions, the VRES and load profiles were based on the weather year 2004, which we also used as the representative year for other studies, as it was a weather year with a median VRE production.

In a decarbonized Dutch economy, the demand for electrolytic H_2 is expected to grow significantly [229]. We do not explicitly model sector coupling but assume electrolyzer capacity to be 6.7 GW in 2030 and 37.4 GW in 2050, based on analyses made with the COMPETES model with the same input data as used for this study [1].[4] We model electrolyzers together as a large load shedder that consumes electricity when the price is below the H_2 import price, corrected for the conversion electrolyzers' conversion efficiency of 74%. Thus, the electrolyzers' maximum willingness-to-pay represents their opportunity costs of providing H_2 (cf. [230]). Because in AMIRIS it is only possible to simulate one load shifter at a time, we simulated EVs and HPs as inflexible, although they have a significant flexibility potential. We chose to model industrial electric heating demand as the load shifter in AMIRIS because the heat could be stored. We set the willingness to pay equal to the opportunity cost of using an NG boiler. Industrial peak consumption was taken from COMPETES results, which increased from 3.1 GW (and 9.6 TWh) in 2020 to 3.6 GW in 2030 and 6.2 GW (and 30.6 TWh) in 2050. We model explicit demand-side response (DSR) as a load shedder with an activation price of 1500 Eur/MWh. The DSR share increases linearly from 3% in 2020 to 11% in 2050. Finally, involuntary load shedding (LS) occurs at the current day-ahead market price cap of 4000 Eur/MWh.

4.4.4. CO_2 prices

The Netherlands has a goal of 100% carbon-free electricity production by 2035 [231]. We do not model a constraint based on CO_2 emissions but instead apply a CO_2 price that increases linearly from 22 Eur/ton in 2020 to 500 Eur/ton in 2050. (Cf. Table 4.6 in the Appendix.)

4.4.5. Scenarios

We increased the price of hydrogen to 116.9 Eur/MWh, based on [232]. This is substantially higher than in our previous publications [62, 135], in which we assumed a H_2 import price of 45 Eur/MWh by 2050 [119]. In recent years, the price expectation for H_2 has increased, as is also illustrated by [233], which estimates the H_2 price to be higher than 10 Eur/kg [5]. We assume the H_2 price to decrease linearly from 2020 to the assumed 2050 levels. Similarly, the biomethane price is assumed to decrease linearly, while the rest of the fuel prices remain constant. (Cf. Table 4.6 in the Appendix.) We test the sensitivity of the results to the H_2 price for the EOM scenario.

[4] In this specific COMPETES analysis, cross-border transmission capacity was set to zero to simulate the same situation as we describe here. As a consequence, the electrolyzer capacities are significantly higher than in other studies. The national climate agreement includes an ambition to scale up electrolyzers to approximately 500 MW by 2025 and 3 to 4 GW by 2030.

[5] However, this study does not consider the economics of scale or technological advances that could lead to lower H_2 prices.

To study the interaction between CRMs and decarbonization targets, we test three levels of CO_2 emission limits for technologies that are allowed in the CRM: one in which there is no CO_2 limit, one where CO_2 limit is constant, and one in which the limit decreases linearly towards 0 in 2050, as specified in the last column of Table 4.1. Although investors do not consider a future tighter emissions limit during their investments, they have a 14-year look-ahead of the CO_2 price.

We allow different technologies to participate in the CRMs. In CS, we allow all dispatchable power plants to be eligible (NG and H_2 turbines, nuclear coal, and bioenergy power plants). The intention for an SR is that plants are seldom activated; for this reason, all dispatchable technologies other than nuclear and batteries are allowed to participate. Nuclear plants are excluded because they cannot ramp up quickly, and batteries may not be available long enough. Moreover, batteries can participate in the wholesale and ancillary services markets instead. For the CM, we simulate two sets of scenarios: one in which only dispatchable power plants are allowed to participate (to make it comparable with the other CRMs) and another in which VRES and batteries can also participate. The derating factor (DF) is calculated endogenously in the latter case. (Cf. Section 4.3.)

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Table 4.1: Overview of the scenarios. In the scenarios' names, the subscript VRE specifies if VRES and BESS can participate in the CRM, and the subscripts “nolimit” , “fix”, and “decreasing” refer to the CRM emission limit. The “year” column indicates the years in which the auction is cleared in advance. The scenarios in bold emphasize the comparison of the CRMs that are compared with each other in section 4.5.3

Name	H_2 price	CRM	year	VRES and BESS	endogenous DF	CO_2 limit
EOM_lowH2	low	EOM				
EOM	high	EOM				
CM_nolimit	high	CM	Y+4	no	no	no
CM_fix	high	CM	Y+4	no	no	fixed
CM_decreasing	high	CM	Y+4	no	no	decreasing
CM_VRE_nolimit	high	CM	Y+4	yes	yes	no
CM_VRE_fix	high	CM	Y+4	yes	yes	fixed
CM_VRE_decreasing	high	CM	Y+4	yes	yes	decreasing
SR_nolimit	high	SR	Y+1	no	no	no
SR_fix	high	SR	Y+1	no	no	fixed
SR_decreasing	high	SR	Y+1	no	no	decreasing
CS_nolimit	high	CS	Y+1	no	no	no
CS_fix	high	CS	Y+1	no	no	fixed
CS_decreasing	high	CS	Y+1	no	no	decreasing

4.4.6. INDICATORS

We use the same key performance indicators (KPIs) as in our previous publication [135]:

- Adequacy-related KPIs:
  - Energy Not Served (ENS) (MWh/year): Load that cannot be served. We distinguish between voluntary shedding (DSR) and involuntary shedding; the latter occurs at a price level of 4000 Eur/MWh and is referred to as load shedding (LS). Electrolyzers and DSR are modeled as load shedders but are not counted as ENS or LOLE.

- Loss Of Load Expectation (LOLE) (hours/year): number of hours in which resources are insufficient to meet the demand.
- Hydrogen production (MWh): Power consumed by electrolyzers to produce hydrogen.

• Financial KPIs for year y:

- Weighted averaged yearly electricity prices (Eur/MWh), in which p_h and q_h are the electricity price and generation in hour $h \in H$, respectively:

$$\overline{p_y} = \frac{\sum_h^H p_h \cdot q_h}{\sum_h^H q_h} \tag{4.1}$$

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

$$C_y^{CRM} = p_y^{CRM} \cdot q_{y,g} \qquad \forall g \in G^{CRM} \tag{4.2}$$

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

$$L_y = \frac{CAPEX \cdot D/E}{\frac{1}{i}(1 - \frac{1}{(1+i)^{T_{\mathrm{EL}}}})} \tag{4.3}$$

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

$$DP_y = \frac{CAPEX \cdot (1 - D/E)}{T_C} \tag{4.4}$$

- Weighted average CRM Costs (Eur/MWh):

$$\overline{p_y^{CRM}} = \frac{C_y^{CRM}}{\sum_h^H q_h} \tag{4.5}$$

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

$$C_y^{consumers} = \overline{p_y} + \overline{p_y^{CRM}} \tag{4.6}$$

- Total system costs (Eur):

$$C_y^{society} = \sum_g (VC_y + FC_y + L_y + DP_y) + ENS_y \cdot \overline{VOLL} \qquad \forall g \in G \tag{4.7}$$

The total system costs represent the total cost of generation plus the cost to consumers of any unserved energy. The $\overline{VOLL}$ is the weighted average VOLL over all consumer groups in Table 4.3. For CS, $\overline{VOLL}$ is the weighted average VOLL of unsubscribed demand sections.

– Normalized annual NPV (Eur): The annual NPV is calculated assuming that revenues and costs remain constant for each operational year.

$$CashFlow_y = \begin{cases} -DP_y & \text{for} \quad 0 \geq y \geq T_C \\ p_y \cdot q_y + C_y^{CRM} - FC_y - VC_y - L_y & \text{for} \quad T_C > y \geq T_C + T_{EL} \end{cases} \tag{4.8}$$

The debt interest rate ρ was the same for all technologies

$$NPV_y = \sum \frac{CashFlow_y}{(1+\rho)^y} \tag{4.9}$$

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

$$nNPV_y = \frac{NPV_y}{K} \tag{4.10}$$

4

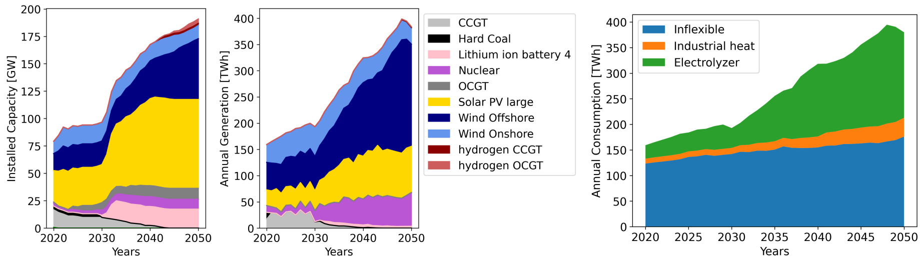
4.5. RESULTS

This section starts in Section 4.5.1, presenting the results for an EOM in which we test the impact of the H_2 price. In the subsequent sections, we present the transition simulations with a capacity market (CM), a strategic reserve (SR), and capacity subscription (CS), each with different CO_2 limits for the plants that are allowed in the CRM (Section 4.5.2). Finally, we compare the CRMs with a fixed CO_2 limit in Section 4.5.3, as specified in bold in Table 4.1.

4.5.1. ENERGY-ONLY MARKET

Figure 4.1a depicts electricity generation capacities and the annual generation mix by technology. During the first simulation years, mainly solar PV and wind offshore were installed to cover the increasing demand. Peaker plants (OCGT) gradually replaced CCGT plants as a result of controllable generation plants' declining utilization hours. Coal plants were decommissioned by 2035 before the end of their lifetimes, per public policy decision. They were replaced by solar PV, nuclear plants, and batteries. Although PV was the technology with the largest installed capacity, wind offshore was the one with the largest energy production. In the last year of the simulation, which was based on weather year 2010, the wind profiles were particularly low, which explains the decrease in generation.

As explained in Section 4.4.3 and as shown in Figure 4.1b, starting in 2030, we simulated a steep increase in the electricity demand of electrolyzers such that by 2050 it had reached almost half of the total electricity demand. In contrast, inflexible demand, including EVs and HPs, and flexible demand, representing industrial heat demand, increased only moderately. The increase in electrolyzers' demand caused the rapid installation of VRES and batteries.



(a) Left: Installed capacity. Right: Annual Generation by technology

(b) Electricity consumption by sector

Figure 4.1: Electricity, capacity and generation in an Energy-Only-Market (EOM) scenario with a high H_2 price of 117 Eur/MWh.

Fig. 4.2 compares installed capacities in the EOM scenarios with a high and low H_2 price. With a higher H_2 import price, domestic H_2 production becomes more attractive, to such an extent that by 2050, electricity generation capacity (at 190 GW) is 47 GW higher than in a scenario with a low H_2 price (143 GW). In addition to the higher H_2 price, the higher generation capacity levels increased the total system costs by 17.6%, costs to consumers by 4.9%, and VRES curtailment by 171% (see Table 4.7). However, these cost figures do not reflect the societal benefits of increased domestic H_2 production, which reduces import dependence. The average annual electricity demand of the electrolyzers over the last five simulation years was 177 TWh, which would be equivalent to 7.12 million tons of H_2 [6]. This was 85% higher than in the scenario with a low hydrogen price, in which 3.83 million tons of H_2 were produced. If the H_2 would be produced at the same level in both scenarios, producing H_2 locally would avoid imports of 5.79 bn (considering the low H_2 price of 1.51 Eur/kg), which is more than double the difference of the 2.57 bn in total system costs between both scenarios. [7]

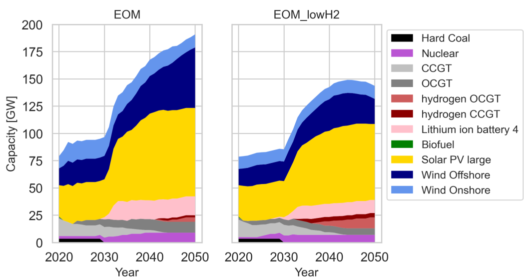


Figure 4.2: Installed electricity generation capacities by technology in EOM scenario with a H_2 price of 117 Eur/MWh (left) and EOM_lowH2 scenario with a H_2 price of 45 Eur/MWh (right)

Figure 4.3 shows the yearly distribution of electricity prices below 350 Eur/MWh. In

[6] Calculated with an electrolyzer efficiency of 74% and low heating value of 33.3 KWh/kg

[7] However, our model does not capture a change in electrolyzer capacity with a changing H_2 price. A study by Johanndeiter et al. reveals that with high H_2 prices, H_2 imports decline from 70 to 10%, leading to more volatile H_2 prices and higher, more volatile electricity prices [230].

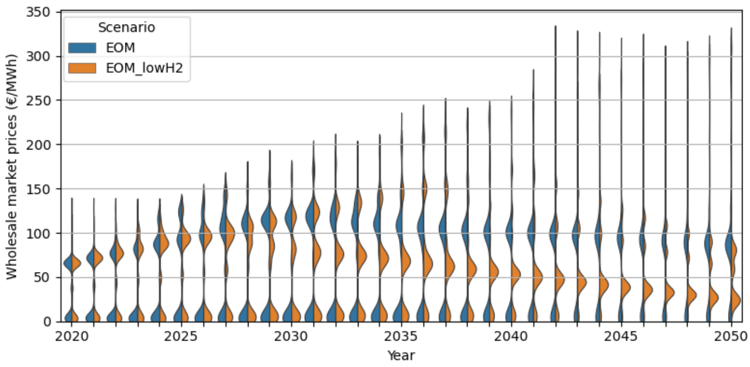


Figure 4.3: Distribution of electricity prices by year, excluding prices above 350 Eur/MWh, where the density is proportional to the number of estimations. The bandwidth of the Kernel estimate of the density function was determined using the Scott method.

the first years, the density of prices near 0 Eur/MWh, i.e., at the marginal cost of vRES, was high, but with increasing flexibility, the frequency of such low prices diminished. Natural gas turbines created a second peak in the price distribution around their variable cost of 60 Eur/MWh, increasing between 2020 and 2032 due to increasing CO_2 prices. A third cluster of prices that results from the activation of electrolyzers starts at 129.9 Eur/MWh in 2020 and linearly decreases to 86.5 Eur/MWh in the high H_2 price scenario and to 33.3 Eur/MWh in the low H_2 scenario. (We assume that electrolyzers are activated at their opportunity cost, as described in Section 4.4.) As illustrated in Figure 4.1b, natural gas turbines were rarely dispatched, with a capacity factor of less than 5% in the years after 2040. In contrast, electrolyzers set the price more frequently, replacing thermal power plants in their role of providing price stability.

Analyzing the weighted average electricity prices, in the scenario with a low H_2 price, prices were higher until 2026 because less VRE and more NG-OCGT were installed. After 2040, when electrolyzers dominate the price setting, prices became lower than in the high H_2 price scenario, and by 2050, they were 20 Eur/MWh lower. See Figure 4.4.

The investment algorithm used a median VRE production profile, as was described in Section 4.4. However, this reference weather year also had milder temperatures, and therefore, the correlated heat demand was low compared to other years. For this reason, the realized peak demand was higher than the expected peak demand during many weather years, resulting in significant volumes of energy not served (ENS) in both EOM scenarios. The highest ENS occurred in 2025 and 2027, as illustrated in Figure 4.4. These years were based on 1985 and 1987, which presented low VRE capacity factors. The low level of flexibility in the first simulation years further contributed to the shortages.

Comparing the two H_2 price scenarios, the volume of load that was shed was higher in an EOM with high H_2 prices, where we observed shortages above 20 GWh and 20 hours. With high H_2 prices, more VREs capacity was installed, but from 2030, the capacity of dispatchable capacity (turbines, biofuel, and nuclear) increased together with more batteries (which complement VREs better). Overall, the volume of shortages in the

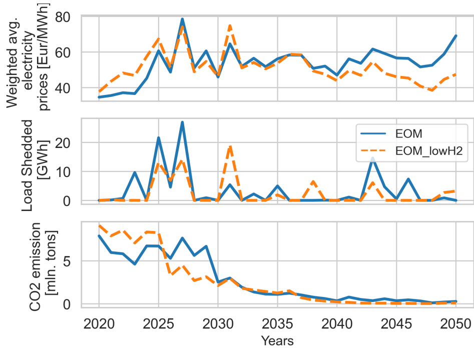


Figure 4.4: Weighted average electricity price (top), involuntary load shedding (middle), and CO_2 emissions (bottom) in a scenario with a final (2050) H_2 price of 117 Eur/MWh (EOM) and a scenario with a H_2 price of 45 Eur/MWh (EOM_lowH2).

4

EOM scenarios confirms the need for a CRM.

The lower part of Figure 4.4 compares the emissions in the two scenarios. With a low H_2 price, the investments in nuclear energy were slower before 2025 and faster afterward, which explains the difference in emissions. A low H_2 price would allow H_2 turbines to be installed earlier, reaching almost zero emissions by 2043. However, lower H_2 import prices would lead to lower generation capacity, lower local H_2 production, and, thus, lower total electricity system costs (but higher total H_2 import costs).

Overall, the demand for domestic H_2 production, which depends on the H_2 import price, has a large influence on the electricity demand. High imports at a low price lead to less electricity generation and lower costs. On the contrary, with high H_2 prices and low H_2 imports, electricity demand is higher due to the increased local hydrogen production. However, the increased capacity of VREs can partially compensate for the higher hydrogen price. As described in Section 4.4, we now consider the higher H_2 price assumption to be more realistic. Therefore, we assumed a high H_2 price in the rest of the simulations.

4.5.2. The performance of CRMs under different CO_2 price scenarios

In the following, we compare the results of all scenarios within the different CRMs, with respect to the installed generation capacities and the other KPIs that were presented in Section 4.4.6 in different CO_2 price scenarios.

Capacity Market

Figure 4.5 shows the differences in installed capacity for the final simulation year, relative to an EOM, under various CO_2 limits (denoted by “CM_nolimit”, “CM_fix”, “CM_decreasing”) and VRES and BESS participation in the CM (denoted by “_VRE”). It shows that with a decreasing CO_2 limit, more H_2-OCGT and fewer H_2-CCGT and NG-OCGT plants are installed, independent of technologies under the CM. On the contrary, without a CO_2 limit, the capacity of NG turbines increases. The earlier installation of NG-OCGT plants delayed the installation of nuclear plants and allowed for the installation of more bat-

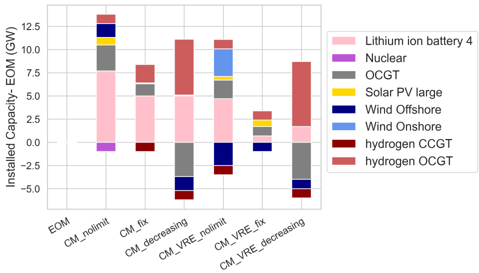


Figure 4.5: Differences in installed generation capacity by technology in the last simulation year for each capacity market (CM) scenario relative to the EOM scenario

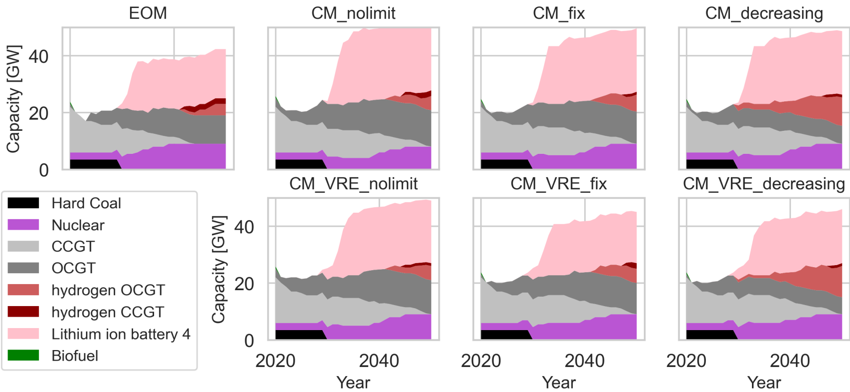


Figure 4.6: Annual installed capacity of dispatchable technologies and batteries in the CM scenarios.

teries, even though they were not allowed to sell capacity credits. Figure 4.6 depicts the yearly installed capacity mix of dispatchable technologies and batteries from 2020-2050. Allowing VRES and BESS to sell capacity credits resulted in slightly more investment in NG-OCGT in the initial years (2020-2025) and thereby lower ENS. Similar to our previous study, a CM reduced shortages significantly throughout all simulation years and in all scenarios, compared to the EOM scenario, as illustrated in Figure 4.7.

We did not simulate early decommissioning in case of insufficient profitability; power plants can extend their lifetime, but not reduce it. Had we done that, the high CO_2 price scenario could have caused a double capacity devaluation. As a study of Frontier Economics [234] explains, non-eligible power plants (NG-OCGT) would be decommissioned sooner and replaced with cleaner technologies (NG-CCGT). Yet, these could also become unprofitable soon thereafter and be decommissioned prematurely as well. Second, while in our model we assumed that investors consider a future CO_2 price 14 years in advance, they do not account for the fact that they would no longer be eligible for CM revenues. Otherwise, there could have been fewer investments in NG-OCGT turbines. This illustrates the need for policies to be announced well in advance to avoid stranded assets.

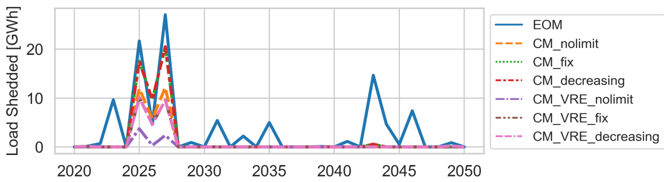


Figure 4.7: Energy not supplied with capacity market (CM) scenarios

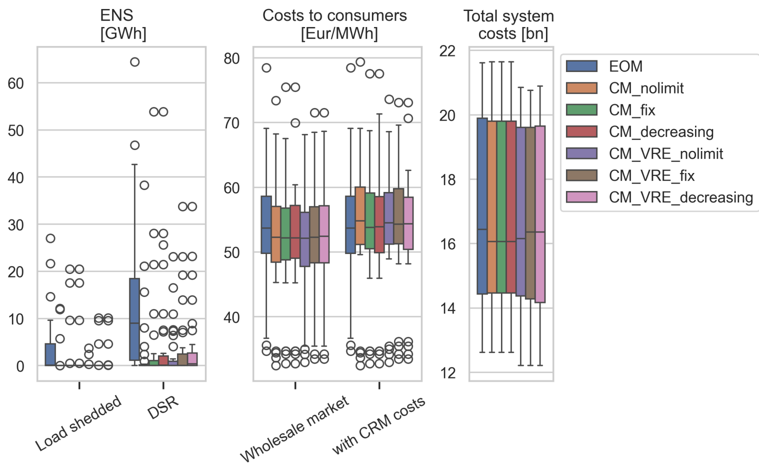


Figure 4.8: Boxplots of yearly simulation results. Left: Energy not supplied (ENS). Center: Average costs to consumers in the wholesale market and with capacity remuneration (CRM) costs. Right: Total System costs

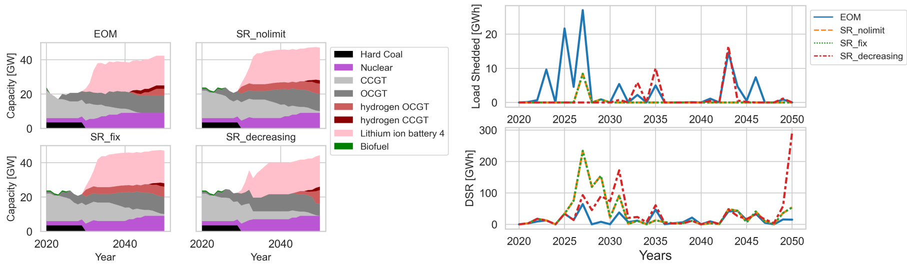
Figure 4.8 (center) illustrates how the reduction in shortages leads to fewer scarcity prices and, therefore, lower average wholesale market prices, compared to an EOM, in all CM scenarios. Nevertheless, the total costs to consumers (which included the CRM costs) were slightly greater with CM than with an EOM. However, as we showed in a previous study [135], the costs to consumers could be reduced with reliability options. The CRM costs were lower with a decreasing CO_2 limit as the target volume was smaller because CO_2-intensive technologies cannot participate.

The total system costs were lower with a CM than with an EOM, independent of the CO_2 limit. Without a CO_2 limit, total costs were lower than with CO_2 limits because NG turbines were used for more years and replaced by fewer new H_2 turbines, as shown in the right side of Fig. 4.8. However, over the 30 years, total emissions were 0.88 million tons higher in comparison to the fixed emission limit and 2.12 million tons higher than with a decreasing CO_2 limit.[8]

Strategic Reserve

An SR effectively mitigated shortages in all scenarios. In our simulations, we assumed that investors account for SR volumes to be the same as in the investment year. As the

[8]As a reference, the simulated annual CO_2 emissions in 2020 in an EOM was of 7.89 million tons.



(a) Annual installed capacity of dispatchable technologies and batteries.

(b) Energy not supplied. Top: Involuntary load shedded. Bottom: voluntary load shedded (DSR)

Figure 4.9: SR scenarios

plants in reserve are activated after the DSR, there was more DSR activation (cf. Figure 4.9b) and more prices at 1500 Eur/MWh (DSR activation price) than with an EOM, thereby incentivizing more capacity.

With all SR scenarios, involuntary shortages were significantly reduced during the years with low VREs and low flexibility (2025 and 2027), as illustrated in Figure 4.9b. With a decreasing CO_2 limit, from 2027 only NG-CCGT plants were accepted in the reserve, and their lifetime was prolonged longer than in other scenarios. Even if NG-OCGT plants were no longer accepted in the SR, these generators were profitable outside of the reserve, resulting in higher installed dispatchable power plants and lower shortages. [9]

We model an SR in which the plants with the highest operating costs (OCGT) entered the reserve. However, with high VRES, the base-load technologies would be the plants with the highest missing money and the first technologies to be decommissioned. If these plants with the highest missing money (NG-CCGT) were to enter the SR, instead of higher operating costs (OCGT), could result in higher payments for their fixed costs but higher effectiveness in reducing shortages.[10] However, the fact that NG-OCGT plants would operate for more hours than more efficient NG-CCGT plants in reserve can be economically inefficient.

Investors did not foresee that NG-OCGT would no longer be eligible for the SR and, therefore, invested in this technology instead of H_2 turbines. After NG-CCGTs were no longer accepted, there were no more plants that could enter the reserve. Decommissioning CCGT plants by 2033 reduced dispatchable capacity compared to an EOM, resulting in increased shortages until 2035. This could be a real issue during the transition: there might not be enough power plants to enter the reserve if decreasing CO_2 limits are not announced many years in advance. In the other SR scenarios (fixed and no CO_2 limit), H_2 turbines were installed earlier because of high scarcity prices, and some NG-OCGT turbines were decommissioned earlier.

With a fixed emissions limit and no limit, NG-CCGT plants were replaced by new NG-OCGT and H_2-OCGT turbines by 2026, as illustrated in Figure 4.9a. However, with a decreasing CO_2 limit, CCGT plants remained available longer but were suddenly decom-

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10 In reality, in SR auctions, generators might bid their missing money and not be chosen by their operating costs.

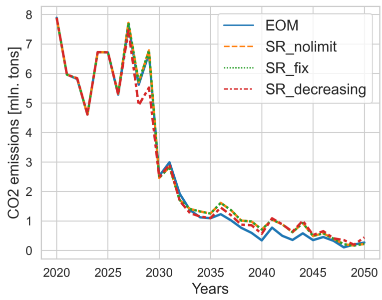


Figure 4.10: Total emissions with SR scenarios

missioned by 2033. They were replaced by new NG-CCGT, thereby delaying H_2-OCGT installation by 15 years. In the last years, the installation of H_2 turbines led to a decrease in profitability and decommissioning of OCGT turbines, which exacerbated DSR activation, as illustrated in Figure 4.9b. In the SR_decreasing scenario, the higher capacity of CCGT kept emissions a bit lower than the other SR scenarios in 2028, as shown in Figure 4.10. Although H_2 turbines were installed later in this scenario, more VRES, nuclear, and batteries were installed, which maintained emissions low.

Adding up the cost of maintaining the plants in the reserve with the revenues from dispatching them at a higher price resulted in negative total costs for the SR operator in most years. With a decreasing CO_2 limit, the costs of the reserve were more volatile; in some years, the SR costs were higher due to the more expensive CCGT plants and H_2-OCGT plants. Yet, in numerous years, the costs were zero due to the absence of plants in reserve, as depicted in Figure 4.11. Overall, as OCGT plants replaced CCGT plants, which have higher fixed costs, the reserve's costs gradually dropped in all SR scenarios.

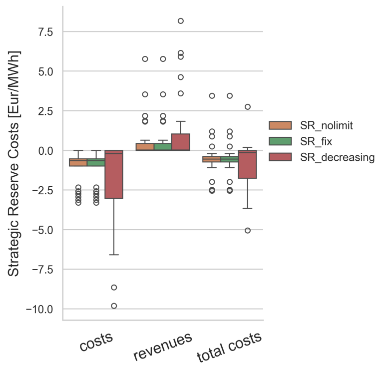


Figure 4.11: Costs and revenues of the SR operator

Figure 4.12 illustrates that an SR almost entirely eliminates shortages but leads to more frequent activation of DSR at a price of 1500 Eur/MWh. Additionally, with reserve plants being dispatched at 4000 Eur/MWh, this resulted in higher and more volatile wholesale market prices than an EOM. Therefore, even with negative extra costs, consumer costs increased, as shown in Figure 4.12. However, the total system costs that included the VOLL were reduced compared to an EOM and were the lowest, on average, with a decreasing CO_2 limit, as shown in Table 4.7.

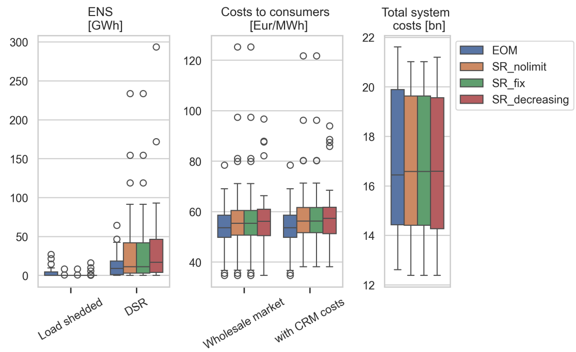
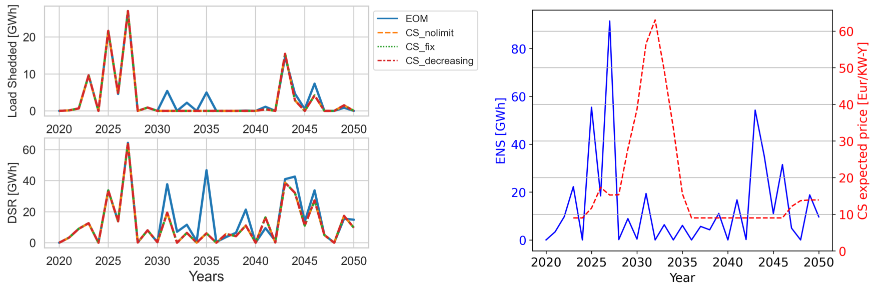


Figure 4.12: Left: ENS. Center: Costs to consumers. Right: Total System costs of SR scenarios with different CO_2 limit

CAPACITY SUBSCRIPTION

In our model, the WTP of consumers for firm capacity depends on experienced shortages.[11] For this reason, CS only reduced shortages some years after consumers had recently experienced shortages, as shown in Figure 4.13a. By 2025, the consumers' WTP and CS prices had been low, which did not incentivize extra capacity to reduce shortages. After the first years of high shortages (2025 and 2027), there were very high CS prices, as shown in Figure 4.13b. Most CS payments were given from 2026 to 2032, i.e. before the CO_2 limit would enter into effect, to NG-CCGT plants, whose lifetimes were extended. Because the decommissioning of CCGT plants was slower, batteries were installed earlier than nuclear power plants, compared to an EOM, as illustrated in Figure 4.14. As a result, there was no difference in the installed capacities depending on the CO_2 limits.

[11] We simulate that investors would consider past CS prices, although in reality, they might be forward-looking.



(a) Energy not supplied. Top: Involuntary load shedded. Bottom: voluntary load shedded (DSR

(b) Left axis: Total ENS. Right axis: Expected CS price by investors.

Figure 4.13: CS scenarios

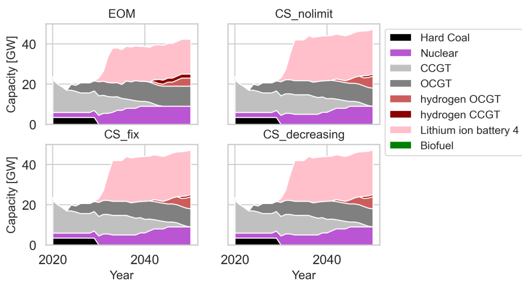


Figure 4.14: Annual installed capacity of dispatchable technologies and batteries across CS scenarios.

In CS scenarios, more capacity led to lower wholesale market prices. However, accounting for the subscription costs, consumers paid more and paid the most without CO_2 limits. With no CO_2 and a fixed CO_2 limit, sufficient generators participated in the auction, enabling most consumers to be subscribed along the simulations. However, with a decreasing CO_2 limit, after 2033, NG plants were no longer eligible for CRM payments. For this reason, the subscription of inflexible consumers fell below 50%, as shown in Figure 4.15. During this period of low shortages, the WTP of unsubscribed consumers remained below the CS price, CS prices remained low, and no additional investments were made. The period with low subscriptions coincided with mild weather years. The low subscription rates, however, could have caused very high shortages if there had been an extreme weather event. In the second period of shortages, from 2033, the WTP of consumers increased, but as we modeled inertia on subscriptions, the subscribers slowly increased their WTP. In the last years, the H_2-turbines' capacity was sufficient for all inflexible consumers to subscribe, but the WTP of some consumers was still low. In short, the decreasing CO_2 limit prevented some power plants from offering capacity credits, which led to low subscription levels and, therefore, lower CRM costs. However, these lower costs came at the risk of higher shortages, which in our simulations were not realized due to coincidentally mild weather. As shown in Table 4.7 on average, CS reduced the total system costs in comparison to an EOM, and the reduction was higher as the

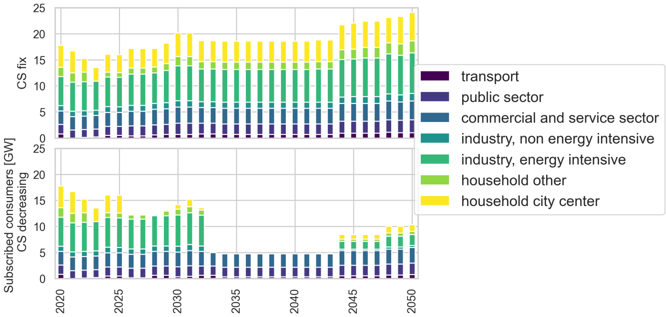


Figure 4.15: Up: Subscribed consumers in CS fix. Down: Subscribed consumers in CS decreasing.

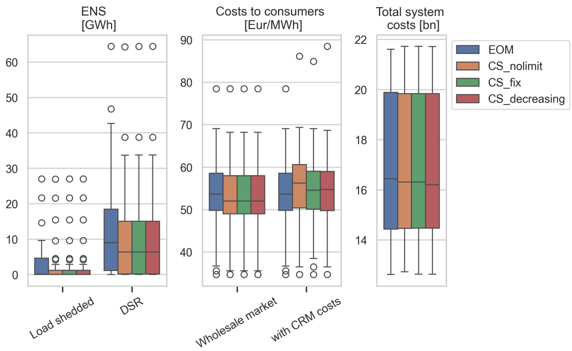


Figure 4.16: Left: ENS. Center: Costs to consumers. Right: Total System costs of CS scenarios with different CO_2 limit

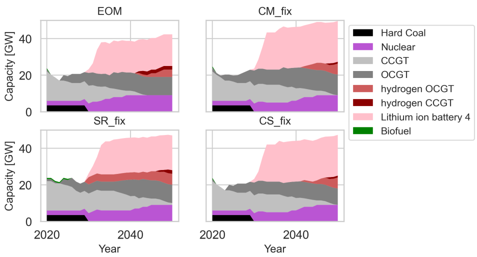
CO_2 limit decreased.

4.5.3. COMPARISON BETWEEN CRMS WITH A FIX CO_2 LIMIT

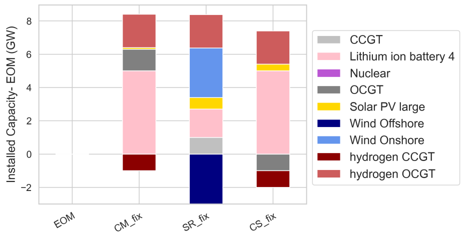
Overall, the degree to which CRMs encourage the installation of more dispatchable capacity determines their efficacy in reducing shortages. Figure 4.18 compares the path of dispatchable technologies installed under each CRM and capacities installed at the end of the transition compared to an EOM. In general, CRMs incentivized more capacities to be installed than an EOM. Particularly, they induced more turbines, which delayed nuclear investments and therefore incentivized more batteries and PV to be installed even if these technologies did not receive CRM payments. Under the CM and CS, H_2-CCGT capacities were reduced, while under the SR, wind offshore capacities decreased compared to an EOM.

In this transition scenario, the SR was the CRM that reduced the most shortages and presented the lowest system costs, in contrast to the previous study, in which CM was the CRM that achieved these results[12]. This finding can be explained with Figure 4.17a, which shows that SR kept CCGT plants longer available during the years with low VREs.

[12]Note the CM presented the lowest median annual total system costs.



(a) Annual installed capacity of dispatchable and batteries



(b) Difference in last years installed capacity by technology relative to the EOM scenario in 2050

Figure 4.17: Installed capacity for each CRM

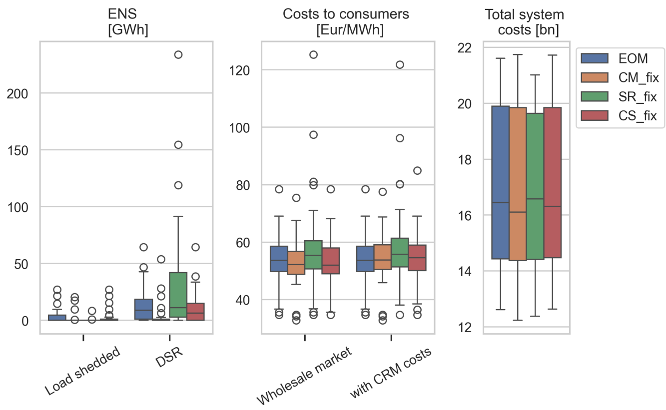


Figure 4.18: Left: ENS. Center: Costs to consumers. Right: Total System costs of CM, SR, and CS with a fixed CO_2 limit

Furthermore, we used a weighted average VOLL of 41555 Euro/MWh (based on Table 4.3 and accounting for a VOLL of 1500 Euro/MWh for the two consumer groups with the lowest VOLL), as a result of which the shortages in these first years had a large impact on the total system costs. This suggests that for a power system in transition, it would be most cost-effective to keep the power plants as long as possible. A CM and CS incentivized new capacity but did not prevent the decommissioning of old turbines, which led to higher shortages in 2025 and 2027.

Similar to the previous study, CM and CS reduced wholesale market costs, while SR caused the highest and most volatile cost to consumers, as by construction, they allow for the occurrence of more scarcity prices. Accounting for the CRM costs, CS caused the lowest costs to consumers. Yet, as explained in Section 4.5.2, this is partially related to the considered weather years that led to low subscription rates.

In the first simulation years, CO_2 emissions fluctuated greatly depending on the weather, independent of the market design. For example, although the total installed capacity of VREs was higher in 2027 than in 2023, the VREs production was lower in 2027, increasing emissions by 3 million tons. After 2030, more nuclear plants and batteries caused a

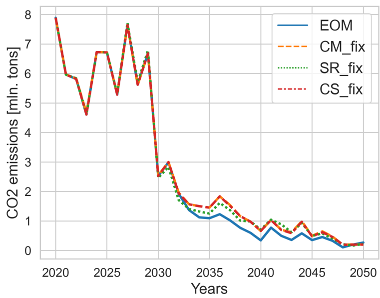


Figure 4.19: Total emissions in CM, SR, and CS with fix CO_2 limits

Table 4.2: Qualitative summary

	EOM	CM	SR	CS
Limiting shortages	0	++	+++ [a]	+
Limiting DSR activation	0	+++	− − −	++
Reducing total system costs	0	++	+++	+
Reducing costs to consumers	0	− −	− − −	−
Reducing electricity price volatility	0	++	− − −	+
Reducing CO_2 emissions	0	− − −	-	− −
Incentivizing demand response	0	− [b]	++	+++
Revenue certainty for investors	− −	+ + [c]	−	−
Avoidance of under/oversizing	0	−	−	+

a) Involuntary shedding was reduced but voluntary DSR increased b) Higher if DSR can participate c) Higher certainty if payments are awarded in long-term contracts

rapid drop in emissions. However, CRMs extended the lifespan of NG turbines, resulting in slightly higher emissions. SR marginally reduced emissions from 2030 to 2040, compared to CM and CS, because hydrogen turbines were installed earlier, replacing OCGT, see Sec. 4.5.2. On average, considering the same weather patterns, relative to an EOM, SR increased emissions by 4%, while CM and CS by 6%. Nevertheless, by 2050, all scenarios presented similar emission levels. The last three indicators from Table 4.2 will be explained in the next section.

4.6. DISCUSSION

Our results indicate that all CRMs effectively reduce shortages compared to an EOM. However, system and consumer costs depend strongly on the calibration of the CRM and the CRM's CO_2 limit. This section discusses the implications of our findings for the role of CO_2 limits in CRMs, the effectiveness of different types of CRMs in the energy transition, and the study's limitations.

4.6.1. THE INTERACTION BETWEEN CO_2 LIMITS AND CRMS

In Europe, the main instrument for CO_2 emission reductions is the Emissions Trading System (ETS), which requires power producers to buy allowances for the CO_2 they emit. However, the resulting CO_2 price also depends on other instruments that influence the power sector emissions, such as renewable support schemes [235]. CRMs pose a risk of inefficiency, as CRM payments could offset the cost of CO_2 emission rights for polluting plants and may prolong the lifetime of fossil-fueled plants. For this reason, the EU implemented a CO_2 emissions cap for generators participating in CRMs.

In this research, we simulated CRMs with annual contracts, which resulted in stranded assets as investments in OCGT plants, which became unprofitable when they were no longer accepted in CRMs. These investments would not have been made if investors had foreseen the reduction in CO_2 limits for eligible plants. On the other hand, awarding capacity payments through long-term contracts may pose a risk of locking in fossil technologies.

The implementation of a decreasing CO_2 limit on eligible technologies for CRMs did not cause reliability issues with a capacity market, yet it increased total system costs. In contrast with a strategic reserve, imposing a limit on CO_2 emissions for eligible plants created a situation in which there were no eligible plants for the reserve in some years, jeopardizing system adequacy. Furthermore, the rapid decommissioning of NG-CCGT plants was followed by investments in NG-OCGT, while investments in H_2 turbines were delayed, which increased emissions. In the case of capacity subscription, the CO_2 restriction meant that there was not enough capacity for all consumers to subscribe over several years. The results did not show more electricity shortages in years with low subscriptions. However, this was due to the coincidental mild weather in those years.

With a generation capacity mix that was based on the Netherlands, an increasingly strict CO_2 limit on eligible technologies did not compromise the effectiveness of CRMs significantly. However, we simulated a less strict decrease of the CO_2 limit, i.e. a linear reduction to 0 in 2050, while the Netherlands plans to decarbonize the electricity system by 2035. In countries with a more fossil-fuel-intensive energy mix, such as Germany, the Czech Republic, and Poland, the effect of a CO_2 limit on eligible technologies could be greater because it could affect most of their existing capacity, potentially causing early decommissioning of a substantial segment of their power plant fleet. In contrast, if there were no CO_2 limit, carbon-intensive technologies would receive CRM payments in some years, potentially extending their lifetime and contributing to higher CO_2 emissions. The implementation of a CO_2 limit on eligible technologies thus appears necessary for achieving climate goals, but the limits should be implemented carefully planned in advance and in consideration of the specific national market conditions to avoid stranded assets.

4.6.2. PERFORMANCE AND TRADE-OFFS OF CAPACITY MECHANISMS IN ENSURING RESOURCE ADEQUACY

Under our simulation assumptions, SR was more effective in reducing shortages, as it prevented the decommissioning of old NG-CCGT plants during the initial years of scarcity.

[13] In contrast, older power plants may be decommissioned under CM and CS if they are not successful in the auction. This shows the primary benefit of an SR, namely to prevent unprofitable but necessary plants from retiring.

We simulated an SR in which the plants with the highest operating costs entered the reserve and sized the reserve so that shortages were comparable to those under CM and CS. In practice, however, the reserve would instead be sized to ensure that specific unprofitable but system-relevant plants remain online. In our simulations, the reserve size was set to 15% of the residual peak load, which is high compared to other European SRs. For example, in Germany, this value is typically below 5%. [236] We chose the larger size to make the investment signal comparable to that of a capacity market, but in the end, the conclusion is that an SR is not a reliable mechanism for providing long-term investment signals.

The SR resulted in higher and more volatile electricity prices, because the plants in reserve were dispatched only after demand response had been fully activated. This distorted the merit order of generation and demand response. The increased price volatility may also increase the costs of hedging and costs of capital. Nevertheless, the mechanism can incentivize market-driven investments in flexibility through scarcity prices while ensuring adequacy by the reserve. If the activation price is set at 4000 Eur/MWh, the SR should not distort the market, compared to an energy-only market.[14] In power systems without renewables, scarcity prices occur primarily during hours with the highest load. This will no longer be the case in future markets where the price will also depend on wind and solar availability. Hence, it will become more challenging to estimate the SR margin that will be needed to induce sufficient but not excessive scarcity prices.

In our model, scarcity prices under an SR incentivized investments in H_2-CCGT and H_2-OCGT. In reality, it is questionable whether investors would rely on these volatile prices. Yet, an SR can help maintain the availability of fossil generators as long as low-carbon alternatives remain uncompetitive. For this reason, it can serve as a temporary measure in case of a risk of system-relevant dispatchable capacity being decommissioned rather than a primary instrument to ensure security of supply.

We did not test the use of an operating reserves demand curve (ORDC). However, this mechanism has the potential to outperform an SR because it can be designed to gradually increase scarcity prices. It also does not require plants to be removed from the market, allowing them to be dispatched before DSR, thereby improving dispatch efficiency and reducing excessive scarcity prices. However, its volatile activation may persist due to weather-driven variability.

In the long term, a CM provides more secure payments and can be more effective in stimulating investment in clean, dispatchable capacity. This additional capacity can decrease the occurrence of scarcity prices. In our simulations, most payments were awarded to CCGT; older CCGT plants were nevertheless decommissioned before the scarcity years, resulting in increased shortages. For this reason, this mechanism was not

[13] If the critical weather year that drove the delay of decommissioning would occurred in later years, it is possible that CCGT plants would already have been decommissioned, resulting in higher ENS.

[14] An SR can also be activated at a lower price, but this could incentivize DSR and other market participants to bid at a price just below the activation price, distorting the market. Furthermore, the activation of the reserve will exhibit increased volatility, and if the activation price is too low, it may significantly constrain wholesale market revenues. Alternatively, the activation price can be reduced after prolonged times of scarcity.

as effective as SR in reducing shortages. Yet, this result is highly driven by the order of our weather years and the choice of the CM demand curve. It may become increasingly difficult to correctly parametrize the demand curve. The target volume should be reduced by the contribution to system adequacy of non-participating capacity and non-eligible technologies, increasing the risk of under- or overestimating it. Furthermore, a planner needs to choose a technology, the CONE of which is used to determine the price cap, but this tends to be a cumbersome and obscure process [237]. Setting the price cap too high can lead to overpayments, but setting it too low could prevent some technologies from participating in the CM. We simulated hydrogen turbines with capital costs similar to those of current NG plants. However, if these turn out to be more expensive, a price cap based on the current CONE would restrict their participation in CMs. For this reason, constant updating of the CM parameters is inevitable. An alternative approach is for the capacity market demand to reflect the marginal benefit of capacity [237], as capacity subscription does.

Capacity subscription offers consumers a way to reveal their need for capacity. Consequently, there is no need to set the parameters of the demand curve centrally. Moreover, it incentivizes all consumers to activate their flexibility. It may be difficult for some consumers to estimate their demand for firm capacity during scarcity periods and to consider rare, extreme events. In our simulations, consumer overreactions to preceding scarcity events led to volatile capacity prices. A solution may be a minimum subscription volume and a price cap on the subscribed capacity. In our model, generators make investments based on past CS prices. Due to the selected weather years, CS was less effective in reducing shortages. There were a few shortages in the years preceding the scarcity period, so the CS price remained low and did not incentivize additional capacity investments.

In reality, generators may be risk-averse to volatile CS prices and may not be willing to rely on yearly payments. Moreover, consumers may not be willing to subscribe to contracts with durations that are needed to mitigate investors' risk aversion.[15] The absence of long-term contracts would benefit the adaptability of the mechanism but could cause the mechanism not to provide sufficient investment security, especially during the energy transition. CS requires consumers to be flexible, as they need to be able to limit their consumption during times of scarcity or contract more capacity. This means that consumers need to be able to monitor their consumption in real-time or to allow a third party to control it. Furthermore, to avoid overshooting after scarcity times are over, the restriction period should be distributed across a longer period. Initially, consumers may need to be subscribed by default to prevent a risk of undercontracting. For more suggestions about the implementation, refer to [170].

In our simulations, both SR and CS award only yearly contracts to generators, which may not be sufficient to mitigate the investment risk. An alternative for a power system with high demand flexibility is to combine CS with a long-term capacity market. We did not simulate this option, but here we compare it with CS. Germany has recently proposed a combined capacity market (CCM) [190]. In CCM, power plants are awarded

[15]Consumers that could commit to long-term contracts would be more strongly incentivized to do so, as there should be no random curtailment in a market with CS. This partially alleviates the missing market problem, although long-term contracts for energy might still be needed.

long-term contracts through a central capacity market (CCM-C). The certified plants in the long-term market are then offered in the decentralized capacity market (CCM-D). The balance responsible parties (BRPs) buy certificates in the CCM-D or self-fulfill their capacity requirements, incentivizing consumers to reduce their peak load during scarcity times. The plants participating in the CCM-C would be subject to a clawback, unlike those in the CCM-D. The German CCM is envisioned as technology-neutral, while we propose CS only for dispatchable technologies. A second difference is that the idea of CS is that DSR participates implicitly (only on the demand side of the market), while in the German CCM, it could participate on both sides [136, 238]. This could lead to manipulation of the baseline and the need for verification efforts. The complexity of a CCM may lead to uncertainty around the time of its introduction. For example, if the CCM-C is overdimensioned, the prices in the CCM-D could become very low. Likewise, if it is under-dimensioned, then the prices in the CCM-D could be very high [238]. However, an advantage is that the central authority would have information about the marginal value of capacity based on the subscription data from past years.

4.6.3. LIMITATIONS OF THIS STUDY

Because of the long computation times and given that our focus was on the relative performance of CRMs, we tested only a single sequence of historical weather years (1980-2010). We did not account for the impact of climate change on weather, the uncertainty of fuel and CO_2 prices, or different rates on the increase of electrolyzers and VRES. We recommend further investigation of uncertainties arising during the transition, such as the risk of more extreme weather events, fuel price shocks, CO_2 price uncertainty, demand growth, etc. The uncertainty regarding the pace and adaptability of electrification in heating, transport, and industry is expected to increase.

The Netherlands recently increased the goal to decarbonize the power system by 2035 [239]. In our simulations, we did not consider VREs and nuclear subsidies. These technologies were invested endogenously. For future research, we recommend considering the Netherlands' actual expansion plans for offshore wind and nuclear energy. We did not impose constraints on fossil-fueled plants, nor did we model CO_2 prices endogenously. Instead, we modeled a stable, exogenous CO_2 price trajectory. We did not consider CCS, although the technology could be necessary to decarbonize the power system by 2035. We recommend researching the interactions between a CO_2 cap on eligible technologies for a CM and endogenous EU Emissions Trading System (ETS) CO_2 prices. Furthermore, we did not include long-term contracts, which could increase the cost recovery stability but also prolong the lifetimes of depreciated fossil-fueled plants. Further research could investigate the interaction of long-term capacity and energy contracts.

We simulated a power system based on the Netherlands but did not consider cross-border transmissions. Resource adequacy will depend heavily on it; therefore, we recommend investigating the interactions among member states implementing different CRMs. Although the DSR can participate in capacity markets, we do not consider a change in DSR based on price volatility or shortages. For this reason, we do not model DSR participation in CM. In this study, we assumed a linear increase in DSR. Additionally, more levels of DSR can be investigated.

4.7. CONCLUSIONS

During the energy transition, investments in generation will be exposed to high risks due to numerous uncertainties. Dispatchable generators that can provide resource adequacy are particularly exposed to risks, as their annual operating hours will fluctuate with a volatile weather-driven residual demand. Capacity remuneration mechanisms (CRMs) reduce investment risk for dispatchable generators. Applying a co-simulation of two agent-based models, we investigate the effectiveness of three different types of CRMs in the Dutch power system in transition between 2020 and 2050. We simulate a capacity market (CM), a strategic reserve (SR), and capacity subscription (CS) with different CO_2 limits for participating power plants, as well as the reference Energy-Only Market (EOM).

Our simulations showed that the effectiveness of CRMs may be diminished if the CO_2 limit becomes restrictive too quickly. In a CM, the CO_2 limit did not affect the reliability but increased the total system costs. In a CS, the limit hindered some dispatchable plants from being eligible for CS, thus reducing the reliability. In SR, the CO_2 limit also shrank the reserve in later simulation years, but the reliability was not affected because the years with a lower reserve volume coincided with years with milder weather and lower need for reserve. Although a CO_2 limit on technologies eligible for CRM is necessary to avoid remunerating carbon-intensive technologies indefinitely, it should be carefully planned and announced well in advance to mitigate adverse impacts on adequacy. Furthermore, we observed that weather patterns can significantly affect CO_2 emissions, while the market design has a marginal impact on emissions.

To facilitate the cost-effectiveness of the energy transition, the future market design should promote flexibility, including Demand-Side-Response (DSR). With a strategic reserve, this is achieved via scarcity pricing. In our analyses, SR was the most cost-effective mechanism, as it effectively kept old power plants available longer, including the initial years with high electricity demand and low VREs production, which resulted in fewer involuntary shortages and a reduction in system costs. SR incentivized new capacity, but at the cost of distorting the merit order and driving up, and causing more electricity price volatility.

In a power system with more capital-intensive than fuel-intensive generation, keeping financing costs low will make the transition more cost-effective. With an SR, new investments must still rely on uncertain, volatile scarcity prices and therefore an SR may not mitigate investment risk. Similarly, in the case of CS, consumers may not be able to subscribe for several years in advance, leaving investors with a high level of investment risk. However, CS might address the missing market problem by eliminating random curtailment, and it offers a significant advantage by disclosing consumers' value for marginal capacity. [16] In contrast, a capacity market that awards long-term contracts can reduce financing costs. A disadvantage is that it requires centralized parametrization of the demand curve, which may lead to over- or undersizing.

In current capacity markets, consumers may be allowed to participate with their DSR on the supply side, but this may be subject to gaming, and the option is not available to all types of consumers. In contrast, capacity subscription incentivizes all consumers to

[16] In our simulations, consumers bid according to experienced shortages and due to the applied unique weather year sequence a CS was not able to avoid the shortages during the years with low renewables and high demand

exploit their DSR, requiring them to determine the demand for capacity. For this reason, if a power system has a sufficient degree of flexible consumers, a good option could be to combine a long-term CM with a yearly CS. CS enables reliability to become a private good, but the mechanism's efficacy depends on the degree to which the consumers are guided to subscribe to sufficient capacity.

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4.8. APPENDIX

Table 4.3: The VOLL of different categories of consumers [177, 178]

	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 [177] 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. [178] determined VOLLs per consumer group through a production function approach. We applied a factor of 1.5 to account for inflation.

Table 4.4: Technologies data [175]

	Investment costs			Fixed costs	Variable costs	Efficiency	Charging eff.	Discarging eff.	Energy to Power ratio	Technical lifetime	Technical limit
	2020 Eur/MW	2030 Eur/MW	2050 Eur/MW	Eur/MW	Eur/MWh	%	%	%	-	y	y
Biofuel	3030612	3030612	2400000	61676	1.83	0.31	0	0	0	25	12,040
CCGT	935768	882599	850698	27648	4.40	0.60	0	0	0	25	-
OCGT	412000	412000	412000	7423	4.50	0.43	0	0	0	25	-
Hard Coal	3845510	3845510	3845510	61528	3.50	0.43	0	0	0	40	-
hydrogen OCGT	478518	467884	435983	7893	4.79	0.43	0	0	0	25	-
hydrogen CCGT	935768	882599	850698	27647	4.24	0.60	0	0	0	25	-
Lithium ion battery 4	1198000	728000	380000	570	1.80	-	0.92	0.92	4	25	-
Nuclear	7940450	7940450	7940450	111166	3.50	0.35	0	0	0	40	-
Solar PV large	490358	490358	290000	7400	0.50	1.00	0	0	0	25	82,099
Solar PV rooftop	840000	840000	640000	8900	0.50	1.00	0	0	0	25	26,964
Wind Offshore	2120000	1800000	1640000	33000	3.25	1.00	0	0	0	30	70,000
Wind Onshore	1105514	1146645	1090288	12059	1.30	1.00	0	0	0	30	12,000

Table 4.5: Other technologies data

	Max. lifetime extension	Permit time	Lead time	Investment block	Debt interest rate 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 4.6: Fuel prices [175]

fuel	2020	2030	2050
Natural gas	26.81	26.81	26.81
Hard coal	8.93	8.93	8.93
Lignite	6.48	6.48	6.48
Nuclear	1.69	1.69	1.69
Oil	40.68	40.68	40.68
Biomethane	86.00	74.66	50.29
Hydrogen	175.60	156.00	116.90
CO2	22.00	250.00	500.00

Table 4.7: Average and standard deviation of EOM with low and H_2 price, and CRMs with different CO_2 limits.

		EOMLowH2	EOM	CMnolim	CMfix	CMdec	CMVREnolim	CMVREfix	CMVREdec
ENS [MWh]	$\overline{x}$	2392	3439	963	1557	1557	206	789	796
	σ	4878	6592	3136	1557	1557	206	789	796
ENS DSR [MWh]	$\overline{x}$	11882	14801	2930	4159	5307	2521	3772	4001
	σ	18271	17054	8119	11243	11804	5497	8039	8018
LOLE [h]	$\overline{x}$	3	3.26	1.10	1.29	1.29	0.26	0.90	0.94
	σ	5	5.37	3.54	4.08	4.08	0.89	2.81	2.80
Total system costs [mln. Eur]	$\overline{x}$	14411	16977	16779	16779	16779	16625	16649	16641
	σ	1467	2948	2931	2931	2931	2785	2789	2815
Weighted average electric prices [MWh]	$\overline{x}$	51	53.5	51.7	51.8	52.1	51.3	51.9	52.0
	σ	9	9.6	9.2	9.2	9.4	8.5	8.9	9.0
Cost recovery [%]	$\overline{x}$	86	84	86	85	84	86	85	84
	σ	12	20	20	20	20	20	20	20
Cost to consumers [Eur/MWh]	$\overline{x}$	51.0	53.5	54.4	53.6	53.3	54.3	53.8	53.4
	σ	8.8	9.6	10.2	9.8	9.9	9.6	9.4	9.3
VRES curtailment [TWh]	$\overline{x}$	10.0	27.0	31.6	29.5	29.2	29.3	28.2	27.9
	σ	5.0	8.3	8.0	8.4	8.5	8.0	7.7	7.8
Emissions [mln. Ton]	$\overline{x}$	2.51	2.64	2.88	2.80	2.77	2.83	2.80	2.76
	σ	3.08	2.70	2.56	2.60	2.62	2.64	2.62	2.65

		SR_nolimit	**SR_fix**	**SR_dec.**	**CS_nolimit**	**CS_fix**	**CS_dec.**
ENS [MWh]	$\overline{x}$	301	301	1148	2865	2876	2876
	σ	1516	1516	3504	6633	6655	6655
ENS DSR [MWh]	$\overline{x}$	34124	34124	38434	11467	11484	11484
	σ	52790	52790	60223	14615	14638	14638
LOLE [h]	$\overline{x}$	0.42	0.42	1.19	2.52	2.52	2.52
	σ	2.00	2.00	2.95	5.30	5.30	5.30
Total system costs [mln. Eur]	$\overline{x}$	16709	16709	16659	16815	16811	16805
	σ	2734	2734	2787	2949	2952	2952
Weighted average electricity prices [MWh]	$\overline{x}$	58.4	58.4	57.6	52.6	52.6	52.6
	σ	18.1	18.1	14.6	9.3	9.3	9.3
Cost recovery [%]	$\overline{x}$	93	93	93	87	85	85
	σ	24	24	24	19	19	19
Cost to consumers [Eur/MWh]	$\overline{x}$	58.9	58.9	58.4	55.2	54.1	54.3
	σ	17.2	17.2	14.3	10.4	9.9	10.4
VRES curtailment [TWh]	$\overline{x}$	29.3	29.3	28.8	29.7	29.7	29.7
	σ	8.3	8.3	8.1	8.2	8.2	8.2
Emissions [mln. Ton]	$\overline{x}$	2.76	2.76	2.76	2.79	2.79	2.79
	σ	2.63	2.63	2.63	2.60	2.60	2.60

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5

DISCUSSION

This chapter addresses the primary research question about the design of CRMs for future decarbonized power systems in subsection 5.1. Subsequently, in the next subsection, 5.2, some aspects of CRMs that were not simulated but are relevant for policy implications are discussed. Finally, in subsection 5.3, reflections on the methodology and its limitations are discussed, along with potential directions for future research.

5.1. RESEARCH QUESTIONS

- **In a future power system with almost 100% VREs, can an energy-only-market enable resource adequacy?**

  One of the most significant uncertainties in future decarbonized power systems will be the weather. In Chapter 2, we explored the performance of market-driven investments in a stable system subject to 40 weather years. We observed that in contrast to current markets, where the price is mostly set by generators' marginal costs, in future systems, most of the time, the price will be set by the demand, largely from electrolyzers. Compared to a scenario with a constant median weather profile, weather stochasticity could increase the variability of price recovery by a factor of three and electricity prices by a factor of ten. Furthermore, dispatchable technologies presented the most variable returns. Our findings suggest that in an EOM, investors may lack incentives to guarantee reliability across all weather years.. Investments aimed at covering demand during years with low VRE output would fail to recoup their fixed costs. In other words, an EOM might not enable resource adequacy in a power system with almost 100% VREs.

- **What are the strengths and weaknesses of capacity remuneration mechanisms in an almost 100% renewable energy system?**

  After confirming that an EOM might not enable resource adequacy for every weather year, in Chapter 3 we evaluated two of the most common CRMs implemented in

Europe, a capacity market (CM) and a strategic reserve (SR), as well as an innovative decentralized CRM, capacity subscription (CS). Similar to the previous study, we examined weather stochasticity in a power system with almost 100% VREs, based in the Netherlands.

We found that a capacity market was the most cost-effective mechanism. However, in a system with high VREs, the parametrization of the demand curve and the derating factors will become more challenging and might need to be constantly updated, which might be complex, especially if batteries are allowed to participate in the market. Moreover, as VRE production is poorly aligned with scarcity situations, these technologies could be remunerated through other mechanisms, as discussed in Section 5.2.

In a strategic reserve, some plants are taken out of the market and dispatched only in extreme circumstances at the highest market price (4,000 Eur/MWh). The mechanism is more cost-efficient because plants in reserve are dispatched less frequently. In a market with a high DSR share, DSR would be activated before the plants in reserve and could set the price more frequently, increasing the level and volatility of electricity prices. For this reason, this mechanism is only suitable for situations in which certain unprofitable plants must remain operational while new capacity is built.

The last CRM we tested is a not-yet-implemented mechanism that can enable consumers to select their desired capacity during scarcity periods. By letting consumers choose their subscription volume, there is an incentive for consumers to increase their demand response and develop local solutions like energy storage and self-generation. Although CS can potentially unlock the DSR participation, thereby mitigating the risk of over- or under-sizing the capacity margins, there exists a risk that if consumers do not consider the possibility of extreme weather events, they can underestimate their need for capacity, leading to subscriptions at very low levels. This may result in demand fluctuations and unstable CS prices. Furthermore, it may be challenging for consumers to commit to long-term contracts.

On the other hand, investors may refrain from making investments unless they secure contracts longer than a year. Making long-term contracts available as a trading option can significantly reduce capital costs. For this reason, we concluded that a combined capacity market, as recently proposed for the German CRM, where a central authority, such as the TSO, takes the volume risk in the long-term capacity market and then sells the credits in a CS at cost price, could be a solution to unlock DSR, reveal the demand for capacity, and lower the risks for investors. One of the main differences between the proposed combined capacity market in Germany and CS is that with CS, DSR would only participate on the demand side, making it simpler and less prone to gaming. Furthermore, if a CS is implemented with reliability options, where revenues over a strike price are returned, the risk for the central authority can be reduced as windfall profits are avoided, and subscribed consumers would be protected from very high prices.

- **How does the transition from a conventional to a renewable electricity system**

change the requirements for a capacity mechanism?

In a final publication, we tested the same CRMs, an SR, a CM, and a CS, with weather stochasticity, but in a transition scenario from 2020 to 2050. Nowadays, most CRM payments have been given to fossil-fueled technologies. To avoid these mechanisms intervening with the ongoing decarbonization of the power system, the EU Regulation implemented a limit on CO_2 emission rates from generators that receive CRM of 550 g of CO_2 per kWh. In chapter 4, we compared CRMs under different levels of CO_2 limits. In a CM, the CO_2 limit did not affect the reliability but increased the total system costs. In a CS, the limit hindered some plants from being eligible for CS, thus potentially reducing the reliability. In SR, the CO_2 limit also reduced the reserve in later simulation years, but reliability was not affected because the years with a lower reserve volume coincided with years of milder weather and lower reserve needs. Furthermore, during the initial crucial years with low VRE production and high power consumption, SR performed its duty of guaranteeing higher capacity of dispatchable technologies. For this reason, during the transition, this mechanism proved to be the most cost-effective. We recommend that a CO_2 limit on CRMs should be implemented to achieve climate goals, however, this should be done under careful consideration of the possible negative effects on adequacy. Furthermore, we observed that weather patterns can substantially affect CO_2 emissions, whereas the market design has a lower impact on emissions.

In a power system with high share of VRE, the activation of an SR depends not only on peak demand but also on weather conditions. While an SR is relatively easy and quick to implement from a legal perspective, as it only requires instructing the TSO to contract a specified amount of capacity, it can lead to market distortions. We observed that if plants in the reserve are dispatched only after DSR, this can distort the merit order and lead to high and volatile electricity prices. Capacity markets (CM) and capacity subscription (CS) reduce price volatility, whereas an SR may exacerbate it. Such price volatility could encourage innovation and investment in flexibility. However, it is problematic for both large and small consumers, who may find it difficult to plan their generation and consumption investments. Moreover, demand for essential goods and services may be inelastic during times of crisis. During such periods, policymakers are unlikely to accept skyrocketing prices. Therefore, a mechanism that amplifies scarcity pricing, such as an SR, may not be a socially acceptable solution. [9] Moreover, investors may not be willing to rely on scarcity prices that occur only infrequently. Finally, high price volatility can increase financing costs. While high prices can, in principle, provide efficient signals to help society manage shortages, the social impact of prolonged periods of high prices is generally not acceptable. For these reasons, we recommend implementing an SR only as a temporary measure - while a long-term CRM is implemented - when there is a risk of decommissioning system-relevant plants. This appears to be the case in the Netherlands, where 3.8 GW of gas capacity is expected to be decommissioned by 2035 because of economic unprofitability.

To incentivize long-term investments, a capacity subscription combined with a capacity market could be implemented. A central agency could award long-term contracts to generators through a CM and then offer capacity subscriptions to consumers on an annual basis. If a clawback mechanism is implemented, consumers could be protected against sustained periods of very high prices.

5.2. Capacity Remuneration Mechanisms Outlook

This section addresses several relevant aspects of CRMs that were not included in the simulations but are becoming increasingly relevant. Thereby, areas for future research about CRMs are proposed.

Participation of flexible and intermittent technologies

The electricity market amendments recommend supporting the capacity of non-fossil flexibility and introducing a flexibility assessment framework [138]. The regulation indicates that member states that have implemented a capacity mechanism may modify it to encourage the use of non-fossil flexibility, such as energy storage and demand response. In our research, we explored the possibility of remunerating VREs and batteries through CRMs. In chapter 3, we simulated a backward-calculated derating factor (DF) and observed a cyclical variation in the DF of batteries. As more batteries were built, their collective output increasingly overlapped, and their contribution to adequacy decreased due to their limited capacity. This is also seen in real life. For example, in the UK, the DF for batteries has consistently declined since 2017, even if the Equivalent Firm Capacity methodology was changed in 2024 [240]. This reflects the risk of overestimating the contribution of batteries to reliability, especially if the contracts were awarded for many years. Due to their limited energy duration, batteries may not be able to deliver during scarcity. We recommend further investigating other schemes to remunerate batteries as explained in 3. Similarly, the demand curve of capacity markets is based on the net-CONE, and in many European countries, this is defined by the DSR. The evolution of DSR value or the selection of new technologies to define net-CONE necessitates ongoing adjustments to net-CONE, and subsequently, to the demand curve. This demonstrates that while long-term policies may enhance investment certainty, if a CM is implemented, it needs to be continuously adapted.

Capacity remuneration mechanisms across the world are evolving to integrate distributed energy resources (DER) such as behind-the-meter batteries, EVs, and smart thermostats, through demand response aggregators. So far, distributed energy resources are too small to participate individually, and including them would increase competition, reducing the cost of reliability. For instance, in the USA, the FERC Order 2222 requires Regional Transmission Organizations (RTOs) and Independent System Operators (ISOs) to allow aggregated DERs to participate in energy wholesale markets, capacity markets, and ancillary services[241]. However, there are limited studies that simulate the strategic behavior of DSR and batteries across multiple markets and the effect of their increased adoption on their own value.

Although the EU recommends technology-neutral CRM auctions, subsidies should be targeted to technologies that need subsidies and are needed from the perspective of the energy system. Batteries are derated with a broad range of derating factors across countries and time. Their factor typically depends on their power-to-energy ratio. In our simulations, we observed that derating factors can be cyclical, as explained in section 3.6. This can introduce uncertainty into capacity market results. Moreover, in some markets, including the Netherlands, these technologies are already profitable from their other revenue streams (energy arbitrage, ancillary services, grid congestion, tolling agreements, etc). Although these technologies do not currently require an additional revenue stream, they may still need it in the future, especially if their revenues from other markets are cannibalized. Further research should investigate how batteries could be remunerated. One possibility is to establish a dedicated central capacity market exclusively for batteries. A cap-and-floor scheme, similar to the one implemented for long-duration storage in the UK, could be introduced. In addition, more sophisticated mechanisms that preserve scarcity price incentives and avoid moral hazard, such as a revenue collar with a soft cap or a yardstick contract based on a floor proposed by Bilimoria and Simshauser [183], could be further researched.

If batteries do not participate in a CM, their contribution should be discounted from the target volume, thereby increasing the risk of under- or oversizing the market volume. In contrast, with CS, demand sizing is automatic, as consumers who are flexible or have batteries reduce their capacity subscription volume. Moreover, new business models in which battery owners sell their capacity in a decentralized CS could emerge.

Given their limited alignment with scarcity conditions, intermittent technologies may be more effectively remunerated through alternative mechanisms instead of CM. In Europe, wind and solar energy have been remunerated per energy, rather than per capacity, to encourage their maximum production. As these technologies become more cost-competitive, their remuneration has shifted from feed-in tariffs to feed-in premiums. The latest amendments to the energy regulation in Europe recommend promoting Power-Purchase-Agreements and awarding VREs within competitive tendering procedures with two-sided contracts for difference [138]. Although CFDs for VREs are the preferred option, other alternatives are available. For example, Newbery suggests a payment specified in MWh/MW capacity and the strike price set by auctions. [180]. Furthermore, financial CFDs [181] or yardstick CFDs have been increasingly proposed as a solution to mitigate market distortions and appear to be a more effective mechanism for incentivizing VREs. In our simulations, we did not model subsidies for VREs. Instead, we simulated endogenous investments in VREs driven by increasing CO_2 prices and declining CAPEX for these technologies. Further research could investigate the interactions of CFDs with CM and CS, where VRE capacity is based on policy plans. Since AMIRIS already incorporates the CFDs option, this can be easily accomplished using the EMLabpy-AMIRIS co-simulation. Subsidizing VREs would accelerate the deployment of VRE capacity, thereby reducing the profitability of gas-fired power plants and increasing the relevance of introducing CRMs.

LOCATION AND TEMPORAL SIGNALS

The development of transmission grids is progressing more slowly than required, posing a significant challenge to the energy transition. Splitting a market can more accurately represent the local value of supply and demand, taking into account the grid constraints. This improves market signals as generators are incentivized to be built near areas of high demand, and the demand is incentivized to develop near regions with abundant renewable energy and lower electricity prices. ENTSOE recently remarked on the benefits of splitting the German-Luxembourg market into five zones, thereby reducing redispatch costs and bringing an economic annual benefit of 339 million euros, as around 50% of redispatch costs could be reduced. [242] In Germany, the redispatch costs in 2023 exceeded 3 billion euros [243]. In contrast, a market split in the Netherlands would make little difference; however, a split in Germany would result in 2% lower electricity prices in the Netherlands [242]. However, the German market splitting does not come without difficulties. Some of these include reduced market liquidity, higher transaction costs, and, most importantly, political opposition due to expected higher costs in the South, where heavy industry is located. Furthermore, it is unclear if the splitting will be necessary once the planned power transmissions are built. Although it is uncertain if a market split will be politically accepted in Germany, capacity markets can help alleviate the problem if they are designed to incorporate a locational signal.

Nowadays, capacity markets can cause locational distortions, where distant sites are overrewarded if all plants of a single technology are assigned the same derating factor (DF) [180]. One solution could be to distinguish DF according to location. Additionally, capacity markets could be cleared on a per-zone basis. This is already done in some capacity markets, i.e. PJM and Italy, although this could reduce the market liquidity. Another option is to give preference to capacities that are needed in a zone or to contract those plants in areas outside the market where they are needed, as in Ireland [160]. However, in countries with no zone splitting, such as Germany and the Netherlands, this is not an easy task. Building more hydrogen plants in the south of Germany could require more hydrogen pipelines. Hence, the coordination of electricity and hydrogen infrastructure is necessary. Similarly, if DFs are static over the year, then the correlation effects can be ignored [180]. For this reason, DFs could be calculated monthly or seasonally. Additionally, CRMs can be seasonal, as seen in France and Sweden [13].

Article 26 of the EU electricity regulation [29] stipulates that member states shall allow cross-border power plants to participate in their auctions. Introducing a CRM in one country can affect the reliability of a neighboring country where scarcities might happen simultaneously, and generators have an obligation to deliver in the country with a CRM. Belgium already has a capacity market, and Germany recently announced that a CRM will be implemented by 2028. This could have consequences for the resource adequacy in the Netherlands. Harmonizing CRMs across Europe remains a challenge because each member state has different reliability standards and if a CRM is in place, the DFs are calculated in a different manner. Even if the DF calculation were harmonized, the DFs per technology would remain different, as they depend on the energy mix, which varies widely across member states.

INTERACTION WITH OTHER MECHANISMS

Electricity market designs aim to maximize the efficiency of existing resources. In a future weather-driven power system, reducing peak demand through consumers' flexibility will be essential. This can be achieved through several mechanisms, and the interactions among them should be further researched.

As EVs, heat pumps, and artificial intelligence proliferate, it is becoming easier to incentivize short-term consumer flexibility through dynamic retail tariffs. The EU's Clean Energy Package encourages dynamic pricing. From 2025, in Germany, energy suppliers that have more than 100,000 clients should offer RTP tariffs, according to the § 41a of the Energy Industry Act [244]. Boom and Schwenen [245] showed that RTP increases welfare if the majority of consumers participate. Risk-averse consumers who choose fixed tariffs may have little incentive to switch; therefore, early adopters could be compensated. Moreover, RTP can also lead to high costs for consumers who may become overwhelmed. Other barriers to RTP and CPP include consumers' exposure to very high prices, concerns about data privacy, and issues related to equity and fairness. Faruqui and Sergici [246] conclude that critical peak pricing (CPP) tends to produce more consistent peak load reductions than RTP due to the higher prices that customers face during peak periods. More recently, Schittekatte et al. demonstrated that a combination of Time-of-Use (TOU) and CPP, managed via automatic load control, can effectively incentivize load shifting without causing extreme volatile prices and unpredictable bills. [247] Although these mechanisms might reduce the peak demand in the short term, it might not be enough to ensure more capacity in the long term. For this reason, it may still be necessary to complement the market design with flexible-enhancing CRMs, such as CS. CPP can work very well with CS. As consumers already subscribe to a short-term capacity, that could be easily linked to a capacity subscription. Furthermore, the clawback could work as a price hedge.

Similarly, dynamic network tariffs or network tariffs with a high capacity component are necessary to incentivize flexible demand and supply. As discussed in chapter 3, CS could also be combined with network tariffs that are based on the same principle of capacity subscription [192], in which case the maximal subscription should be the same for both. In a congested area, consumers could be restricted to a maximum capacity subscription per household.

The amendments to the electricity market design emphasize the introduction of green criteria but also mention that gas power plants could participate [138]. As we simulated in chapter 4, if a CO_2 limit is not planned in advance, this can result in stranded assets. An alternative proposed by Crampton and Ockefelds to enable hydrogen plants to be cost-competitive is to provide a hedge to cover the cost differences between the natural gas price minus the carbon price and the hydrogen price [248]. They argue that the government should bear the risks because the hydrogen price will largely depend on the government's hydrogen subsidies, regulations, and infrastructure. Moreover, the government will decide when hydrogen-ready gas plants should switch to hydrogen.

The future of hydrogen and electricity markets is closely interconnected. Thus, additional research can focus on the development of hydrogen strategies, encompassing hydrogen plants and electrolyzer subsidies, infrastructure deployment for hydrogen, including pipelines and storage, as well as the associated electrical infrastructure.

Capacity Subscription

This dissertation suggests that if a system's degree of flexibility and digitalization is high enough, a capacity subscription could be a suitable CRM. However, this mechanism was evaluated in a simplified manner. Further research can go deeper into the empirical details of its implementation. For example, to explore the ability of consumers to choose their capacity during scarcity and their possibility of committing to yearly or longer contracts. Additionally, how can critical periods and consumption limitations be effectively communicated, such as through in-home displays, or is it better to implement automatic control? How can this be achieved technically? And in which manner is the limitation best accepted? Consumers have a stochastic time-varying overall demand. It would be inefficient to exploit all consumers' flexibility simultaneously. It might be convenient to design the CS in a way that consumers' peak demand is distributed to avoid a rebound effect where demand peaks just after the peak time slot. Previous studies have demonstrated that consumers respond more positively and acceptably when scarcity periods are announced in advance. Similar to capacity markets, CS could also be enhanced with a local component; however, there is a risk that clearing regions would be too small, resulting in a market that is not liquid enough.

The primary risk of this mechanism is the lack of experience with it. The mechanism involves consumer participation, which can be problematic, as many consumers may be price-insensitive and reluctant to accept electricity supply reliability as a private good. We simulated a CS where consumers based their bids on the previous 3 CS prices. This resulted in volatile CS prices, because consumers initially undersubscribed, experienced high scarcity levels, and then subscribed at higher prices, which triggered significant capacity investments and subsequently drove prices down again. In reality, consumers might consider not only past CS prices but also future prices. However, they might ignore the possibility of extreme weather events. Another challenge is that consumers need to be able to translate their needs into a financial metric. Furthermore, consumers may delay their investments in flexibility if CS prices are consistently low and there are no flexibility investments, such as dynamic tariffs, CPP, or TOU rates. An alternative for a combination with a long-term CM could be a floor and cap on the CS price. This approach would provide investors more certainty regarding their investments, notwithstanding the annual contracts.

5

OTHER CAPACITY REMUNERATION MECHANISMS

As explained in 1.4.1, the missing markets and the missing money problems can be remediated with capacity payments, energy payments, or enhanced scarcity pricing with different mechanisms. In this research, I explored market-based mechanisms that incentivize more capacity through capacity payments and scarcity prices.

In recent years, there have been more proposals to incentivize more capacity through hedging obligations for consumers or retailers. Future research could compare CS with CRMs via energy payments, such as affordability options [39], insurer of last resource [31], SFPFC [20], and obligation to hedge. Some of these mechanisms could again forward markets, but at the cost of dampening the price responsiveness of consumers who have hedged their energy costs. Furthermore, an obligation to hedge could pose a greater challenge for newcomers and smaller retailers that may lack the necessary liquidity to hedge. Furthermore, smaller generators might not be able to offer reliable contracts, whereas larger generators can manage a combination of technologies. The obligation to hedge could indeed improve liquidity in forward markets, but wholesale prices could rise if the hedging premium is passed on to consumers.

5.3. REFLECTIONS ON THE METHODOLOGY

Chapter 2 presented the heuristics behind the model developed for this research, EMLabpy. In this section, general reflections about the methodology are discussed.

An electricity market is an effective way of coordinating a power system that is becoming increasingly decentralized. Nevertheless, in practice, a market does not always ensure long-term equilibrium; rather, it incentivizes short-term adaptations. However, most energy planning is conducted using optimization tools that assume perfectly competitive markets and perfect foresight, thereby ensuring long-term equilibrium. Investigating CRMs with an ABM approach proved useful because it enables modeling complex, adaptive systems. With EMLabpy, it was possible to represent power plants as blocks rather than as continuous small volumes, as is done in optimization models. This allowed us to more closely represent CM auctions with volatile results, as seen in reality. Furthermore, the iterative investment decision allowed us to model the situation in which investment decisions are myopic and uncoordinated. In contrast to optimizations that find the most cost-effective solution, as a snapshot. With ABM, it was possible to simulate expansion pathways in which an early investment in one technology alters subsequent investments and cannot be reversed. Furthermore, we simulated that all units were decommissioned after their technical lifetime was over, as its lifetime was extended if they were profitable or entered the reserve. In chapter 4, this allowed us to analyze investment pathways rather than just compare final capacity.

This research was funded by the TradeRES consortium, which aimed to combine different models developed by its partners. Accordingly, we conducted the co-simulation using AMIRIS, a consortium partner's model, which provided a Python wrapper to set up and run it. The development of this model occurred in parallel with this research. At that time, only a single agent's energy storage was possible. For this reason, we simulated electrolyzers as load-shedding units and treated EVs and heat pumps as inflexible loads. At the time of publication of this dissertation, the modelling of heat pumps and multiple flexibility options had been improved, and further research could include these improvements. Instead of developing a new dispatch ABM model, co-simulation allowed us to combine the strengths of existing models. Moreover, the independent development of the energy models allowed a parallel and faster development. Using Spinetoolbox proved advantageous, as it allowed for storing variables in the database, enabling the debugging of individual modules without running the entire workflow. However, a downside was that the simulation time was extended, as the reading and writing were time-consuming and required structuring the data in a format compatible with Spinetoolbox. A co-simulation requires knowledge of the models to identify connection points, and it can be resource-intensive as it requires harmonization of parameters.

The co-simulation methodology was computationally expensive, and to keep the time feasible, some modifications were necessary compared to the original EmLab model. For example, in EmLab, the candidate technologies were tested individually with the block capacity, which requires many iterations per investment decision. To accelerate the simulations, in EMLabpy, we tested several candidate technologies simultaneously, each at 1 MW, and the most profitable technology was then invested in at full capacity. This caused the profitability of the generator to be lower than expected because 100 MW of investments would yield lower revenues than a generator of 1 MW. Furthermore, in the original EMLab, the dispatch was run with a very simple optimization and a segmented load curve of 20 levels, which ran within a few seconds and allowed for many iterations. Another major difference was that Emlab simulated power plants that entered operation after their permit and construction were complete. However, in future power systems, some technologies have a shorter lead time, such as batteries, and if these were installed before the year in which they were planned (Y+4), then investment cycles would be exaggerated as batteries would be installed before the power plants in the pipeline, leading to excessively high capacities followed by periods of insufficient capacity. Hence, in EMLabPy, commissioning was assumed to occur in the year they were planned (Y+4).

5.3.1. Limitations and future research

Modeling energy systems does not aim to produce exact numbers, but rather to identify the factors that exert the greatest influence on possible outcomes. This subsection identifies the most significant limitations that could influence the results of our research.

The EU recommends implementing a clawback, which can significantly reduce CRM costs to consumers. If the dispatchable power plants already receive stable revenues from CRMs, then the scarcity profits should be avoided. Although we simulated a CS with a clawback, we did not simulate a CM with a clawback, also known as reliability options. Scarcity events can occur more often with a high share of VREs, and reliability options could help avoid market power. Future research should compare the CRMs with clawback. In our research, we tested a SR in which reserve plants are dispatched at the maximum electricity price. An alternative is to dispatch them at a high threshold of 500 Eur/MWh, as a recent study suggests [249]. However, this can distort the market as DSR can be incentivized to bid just below that value, and wholesale revenues would be reduced. An alternative is to reduce the activation threshold after a prolongued time of scarcity.

Two large limitations of this study are that we did not simulate cross-border transmission and sector coupling. A co-simulation approach proved useful in leveraging the strengths of two ABMs. However, transferring data between models exponentially increased the computational time, thereby impeding the simulation of cross-border trading and sector coupling. Both will be essential for the energy transition and can significantly influence the need for CRMs. while cross-border transmission can improve resource adequacy and reduce the need for CRMs, some member states may be reluctant to rely entirely on neighboring capacity. However, if neighboring countries implement a CRM, the state without one could face resource inadequacy. As explained in subsection 5.2, the harmonization of CRMs continues to be a challenge and warrants further research.

We modeled flexibility in a simplified manner. We simulated a single DSR level and assumed no EV flexibility. Furthermore, we assumed a static DSR and did not consider that increasing price volatility may increase it. If sector coupling were modeled, endogenous investments in heat storage and heat pumps could also be simulated. However, household DSR can be more complicated to parametrize. In the case of CS, we could not model how consumers would shift their demand as a result of having a CS contract.

However, as we explained in chapter A, the demand side, including electrolyzers and energy storage, will set the price in an increasing manner. Nevertheless, a recent study analyzed the need for backup hydrogen plants in Germany. Even in a scenario with full flexibility from EVs, electrolyzers, heat pumps, and storage, the study confirms that high-volume hydrogen backup power plants will remain essential, and capacity markets might be necessary due to the low operational hours of these technologies [250].

Nowadays, there is a rapid deployment of batteries, which have multiple revenue streams, including ancillary services, congestion management, the intraday market, and implicit arbitrage in wholesale markets. In this work, we only considered the day-ahead market. Future research could apply a co-optimization approach to account for revenue stacking, as is done in practice.

In Chapter 3, we assumed a fixed installed capacity of nuclear 5.6 GW, based on

COMPETES results, under the premise that the investments in this technology are politically triggered and centrally planned. At the time of research (2020-2023), the Dutch government planned 2 power plants; however, the capacity was not determined [251]. In our simulations, the profitability of nuclear energy was largely negative. For this reason, in the subsequent research, presented in chapters 3 and 4, we did not fix nuclear capacity exogenously but instead modeled it as an investment candidate, and no nuclear investments were observed. Future research could compare both scenarios: one that considers policy goals, letting technology capacities serve as variables, and another that considers political decisions. Furthermore, emerging technologies, such as small modular reactors, carbon capture storage, and seasonal thermal storage, could be tested. Moreover, we did not account for renewable energy subsidies, power purchase agreements (PPAs), or hedging contracts. Future research could incorporate an exogenous deployment pathway for offshore wind to reflect its typically subsidized and centrally planned expansion.

We modeled risk-neutral agents that only considered future fuel and CO_2 prices and the median weather year. Agents were myopic and considered CO_2 prices in the next few years. In practice, companies might be more risk-averse and consider a longer time horizon, increasing the need for CRMs.

TradeRES's objective was to compare different models using a unique dataset, and therefore, we used an optimistic hydrogen price 45 Eur/MWh. However, for the sequential publications, we used a higher hydrogen price, although it might still be optimistic. The results in Chapter 4 suggest that a higher hydrogen price could further increase the need for CRMs, as hydrogen-based plants may become more expensive; this could incentivize a higher share of VREs and consequently strong scarcity periods. Alternatively, more natural gas plants could be built, but these would be out of the market as CO_2 prices increase.

In this research, we made several simplifying assumptions about hydrogen, in line with the conventional wisdom at the start of the project (early 2020). We assumed that hydrogen demand will be driven by industry, transport, and imports, so hydrogen prices will be determined exogenously. Furthermore, we did not consider limits on hydrogen transport and storage. Additionally, we did not limit hydrogen production and simulated only two hydrogen prices, based on 2019-2020 assumptions. We determined the electrolyzer's capacity based on an optimal capacity with COMPETES at a low hydrogen price, and for the transition scenario, we assumed a linear increase in electrolyzer capacity. Nonetheless, the transition is unlikely to be linear due to numerous uncertainties. Some of these uncertainties include the level of subsidies, delays in offtake agreements, delays in hydrogen transportation infrastructure, and delays in power transmission lines. Additionally, the green hydrogen price competitiveness depends on sufficient VREs capacity, as low electricity prices are essential. Nevertheless, there is still uncertainty regarding the volume of VREs being installed. At the same time, investments in renewables also depend on the flexible demand level, among others, from electrolyzers. In chapter 3, we noted that importing hydrogen at low prices could result in reduced electricity prices; however, this would entail an ongoing reliance on fuel imports and a diminished energy independence, which is one of the main advantages of the energy transition.

In this study, we only studied the weather variability but did not consider other uncertainties such as fuel price, hydrogen price, CO_2 price, or augmented weather profile volatility due to climate change. Furthermore, to analyze the impact of weather uncertainty, a Monte Carlo stochastic approach would have been ideal. However, this was infeasible due to the co-simulation duration of over 10 hours. Especially in the last publication, we applied a single weather-year sequence, which influenced the results, as discussed in Section 4.6.2. Simulating hundreds of such sequences could yield more robust insights. For this purpose, a unique model would be needed instead of a co-simulation. For this purpose, EMLabpy could be further developed with a simple optimization algorithm or a an investment algorithm could be added to AMIRIS.

Previous research has investigated fossil fuel prices as the main source of uncertainty. We have proven that weather can become a highly relevant source of uncertainty. However, a recent study suggests that a portfolio with an increased share of vREs and energy storage could actually enhance the diversity of tail events, as tail risks can become less correlated (whereas extreme fossil fuel price shocks tend to be more correlated). [252] Hence, it would be interesting to compare a transition scenario that combines both sources of uncertainty, namely extreme weather and fossil fuel price shocks reflecting an energy crisis.

A major source of uncertainty for the profitability of new power plants is the anticipated total installed capacity, which includes both future power plants and the decommissioning of existing ones. One of the advantages of ABM is that it allows for the simulation of myopic investment strategies, rather than rational and optimal decisions. In EMLabpy, we simulated agents that based investment decisions on a future market. However, investors may also consider current and past results when making investments. This has been the case, for example, with batteries. In recent years, the lower costs and high profitability of batteries have led to a record number of installations. Only in Germany have connection requests risen to 160 GW [47]. We recommend simulating a "quick investments" algorithm wherein investors in batteries and PV technologies that can be deployed quickly, ignoring delays from a lack of infrastructure, DSO connection permits, and other regulatory issues, base their decisions on historical performance. In addition, for CS, we assumed that consumers base their bids on the previous three years. However, consumers may not be myopic and could also take future expectations into account when making their bids. Further research could integrate a future price expectation for the consumers

In our simulations, power plants are decommissioned upon completion of their technical lifetime, and if the average profits are positive, their lifetime can be extended. We did not consider the possibility of mothballing or early decommissioning, which can be very relevant for the security of supply. Other ABMs, such as [96], do account for early decommissioning; however, this must be carefully modeled because early decommissioning can be more complex than simply being based on profitability. Although there is plenty of information about the costs of capital per technology. During this research, it was difficult to find information about the maximum technical lifetime extension per technology. The amortization time, based on the generators' lifetime, can significantly affect the profitability of generators. Hence, further research can investigate this.

One limitation of this study was that in a CM, we did not model long-term contracts, as these depend on investors' liquidity and estimation of future prices and price volatility. In our simulations, some investments might have been under an expectation of high CM prices, which turned out to be lower. Moreover, we did not consider the positive effect that long-term contracts have on capital costs. For example, Helistoo et al. showed that increasing the WACC from 3% to 11% led to a 37% increase in total system costs. [253]. Simulating long-term contracts in future research would enable the study of a combined capacity market and its possible complications. For example, as more plants receive long-term contracts, the target volume could be reduced, and capacity prices can become more volatile.

In many energy dispatch models, including AMIRIS, offshore wind is simulated with lower variable costs than solar PV. This can cause solar PV to enter the merit order curve much more often than wind energy. However, wind-powered generators are price takers, meaning they bid zero to enter the market as much as possible and are therefore dispatched as much as solar PV. [1] The fact that in AMIRIS, wind plants are only dispatched after PV plants can explain the high proportion of solar PV in our simulations. Future research could consider a scenario where all renewables are modeled as price takers, bidding zero.

[1] However, companies that own VREs do not always bid zero and can bid strategically. Companies tend to bid at higher prices in times when intraday prices are much higher than the day-ahead market. Furthermore, this arbitrage in sequential markets could become increasingly important [254].

6

CONCLUSIONS

Power systems in Europe are transitioning towards decarbonization. One of the greatest challenges of a nearly 100% VRE-based power system will be securing electricity supply during periods of scarce solar and wind energy, also known as Dunkelflaute. To ensure a reliable electricity supply to meet demand at all times, capacity remuneration mechanisms (CRMs) have been increasingly introduced across Europe's electricity markets. In this dissertation, I compared three CRMs - namely, a capacity market, a strategic reserve, and a capacity subscription - and an energy-only market in an already decarbonized power system and a power system in transition, considering the effect of weather uncertainty. Applying a co-simulation of agent-based models, we focus our research on the Netherlands, where the electricity system's reliability is expected to decline in the coming years. The relevance of this study is underscored by the Dutch government's announcement in early 2026 of a CRM introduction.

In a system driven mainly by intermittent resources, dispatchable generation will be exposed to greater operational and revenue risk, as its activation becomes more uncertain and volatile. Furthermore, as VREs are remunerated through alternative support mechanisms, market prices have been increasingly suppressed during periods of high wind and solar generation. The energy transition entails substantial changes and conveys high uncertainties and risks. Moreover, regulatory uncertainty is among the most significant challenges for the energy industry. For these reasons, a forward-looking policy can help reduce uncertainty and, consequently, lower the cost of capital. Testing market designs for future scenarios is therefore essential to reduce policy uncertainty and improve investors' expectations, thereby supporting the achievement of a decarbonized, affordable, and reliable power system.

To compare market designs, we first analyzed the conventional adequacy indicators. Current performance indicators were conceived in power systems where demand was largely inflexible, and generation was dispatchable. In future power systems, traditional reliability standards, based on a single value of lost load, outage rates, and energy not served, may lose relevance. Adequacy will no longer be about the ability of generation to meet demand under all conditions, but rather the dynamic balance between generation and consumption, thereby shifting the focus from generation adequacy to overall system adequacy.

Due to the rapid growth of renewables, price volatility has increased in the Netherlands in recent years [255]. In a system with a high share of VREs, the demand side will need to become more flexible to balance intermittent generation. As demand increasingly sets marginal prices, scarcity situations will be reflected in high and volatile electricity prices rather than physical electricity outages. If average prices rise above the average power supply cost, this would imply potential windfall profits for generation companies and may signal a lack of investments and an inadequate system. Furthermore, sustained high prices might not be socially acceptable and could trigger regulatory intervention. Price volatility can also indicate an insufficient degree of flexibility and may reflect the system's stress, even if involuntary curtailments are low. Furthermore, price volatility increases investment risks and capital costs. We identified the need to complement technical metrics with an unconventional indicator: market signals such as price volatility and market-based cost recovery. Prices reflect the market's efficiency, and volatile prices can be an early indicator of a lack of system flexibility. Throughout this thesis, we utilized electricity price volatility and market-based cost recovery to evaluate various market designs.

First, we analyzed an energy-only market in a decarbonized power system and found that electricity prices will be predominantly set by demand, particularly by electrolyzers and their willingness to pay, which will depend on the hydrogen price. Furthermore, we demonstrated that the weather will particularly affect the annual operating hours of dispatchable technologies. We showed that if investors were to invest in capacity to guarantee reliability for every weather year, they would not recover their costs. For this reason, capacity remuneration mechanisms will be needed to ensure security of supply in decarbonized power systems.

A strategic reserve can be easily introduced from a regulatory perspective. In the transition scenario, this mechanism was more effective than other CRMs at prolonging the lifetime of plants in the reserve. In this way, it ensured that some gas-fired plants remained available in the initial years, when renewable production was low and demand was high, thereby effectively preventing shortages. These are the primary benefits of this instrument. On the other hand, because reserve units are only activated during scarcity events, price spikes remain frequent and unpredictable, and the merit order of dispatch is likely to be distorted. Although an SR may incentivize investment in flexibility, price spikes are undesirable for consumers and the mechanism may fail to incentivize new investments. Given that this mechanism can be implemented relatively quickly, it can serve as a temporary measure in case there is a risk of essential capacity being decommissioned.

A capacity market can provide more stable investment signals than other mechanisms. Besides the energy trilemma of balancing between decarbonization, sustainability, and economic goals. A market should be designed to allocate risk efficiently. Capacity markets act as insurance, enabling generators to reduce their revenues from scarcity prices in exchange for more certain revenues, thereby reducing their capital costs. However, its effectiveness depends on its parametrization. In a capacity market, a central authority sets the demand level. To find the optimal reserve margin, the cost of new entry is balanced with a single VOLL. However, the VOLL varies across consumer groups, interruption types, and other factors. As these parameters evolve, the reserve margin will need to be constantly adapted. The weather will also complicate the parametrization of the demand curve and the derating factors. However, if capacity payments are awarded through long-term contracts, there may be little room for correction. In this mechanism, consumers bear the costs and are not empowered to choose their desired level of reliability. If a system is oversized, electricity prices may be very low and stable, thereby disincentivizing demand flexibility and leading to high capacity costs. For these reasons, a capacity subscription can be an effective solution to increase generation adequacy while incentivizing DSR. The latest amendments to the European market design state that consumers should be put at the center, protected from high prices, and incentivized to participate with their flexibility. With capacity subscription, consumers choose the capacity they need during scarcity periods, creating a clear incentive to reduce peak demand by shifting their load. Moreover, the net demand for dispatchable capacity is revealed by consumers, rather than determined centrally.

In a decarbonized power system, the choice of CRM will depend not only on the share of VREs but also on the degree of consumer-side flexibility. In a future decarbonized power system, capacity subscription can be an effective alternative to incentivize more investments while enhancing demand-side response. If CS is implemented as reliability options, subscribed consumers also benefit from price protection during scarcity events. As consumers may not be able or willing to subscribe to contracts of multiple years, this mechanism could be complemented with a long-term capacity market in which an intermediary agency would contract capacity for the long term and then sell it annually to consumers.

The energy transition faces the dual challenge of facilitating consumer flexibility and providing long-term investment signals. During the transition, if there is an imminent risk of decommissioning system-relevant power plants, a strategic reserve may effectively prevent their premature retirement, thereby reducing the risk of shortages. However, this mechanism alone may not be sufficient to incentivize new investment and should be seen only as a provisional measure.

Finally, we simulated different CO_2 limits for plants' eligibility across the different CRMs and observed that these limits, as well as the market design, had a smaller impact on CO_2 emissions compared to the weather year. To achieve climate goals, it is necessary to implement CO_2 eligibility limits; however, these should be carefully planned in advance to ensure the effectiveness of the CRMs.

A

Market signals as adequacy indicators for future flexible power systems

The chapter was originally published as L. J. de Vries and I. Sanchez Jimenez: "Market signals as adequacy indicators for future flexible power systems" in Oxford Open Energy. Volume 1 (2022), DOI: 10.1093/ooenergy/oiab007. Formatting has been standardized throughout this thesis.

A.1. Abstract

Existing indicators of electricity system adequacy are not fit-for-purpose for the future power system, but need to be supplemented with economic performance indicators. Reliability standards need to better reflect the price elasticity of increased flexibility. If the average electricity price is well above the average cost of power supply, this can be an indication that the system is not adequate, even if the outage rate does not exceed the current reliability standards.

A.2. Introduction

Existing indicators of electricity system adequacy are not fit-for-purpose for the future power system. The current European resource adequacy assessment methodology uses reliability standards that underestimate the impact of energy storage and flexibility provided by demand response. In this publication, we refer to flexibility as the ability of the system to maintain system stability through changes in generation and demand. (Definition extended from [256].) In a system with a high degree of flexibility, a generation shortage may not necessarily lead to outages but manifest itself through high electricity prices. Demand flexibility increases reliability, but may cost consumers in terms of convenience or, in case of commercial consumers, lost productivity.

Adequacy is the long-term ability of the power system to meet load, in expected and in unexpected conditions [257]. Conventionally, the focus of adequacy assessment has been on the ability of the electricity generation stock to meet demand under all conditions—the term that was used was generation adequacy. The increase in demand flexibility and the introduction of electricity storage technologies means that they can contribute to the energy balance in the system. Therefore, the focus needs to shift from generation adequacy to system adequacy. This also requires a reconsideration of how we measure adequacy.

A.3. EUROPEAN ADEQUACY ASSESSMENT REGULATION

Conventionally, power system planners aimed for a certain capacity margin in excess of expected demand to secure enough generation during peak load moments. This was defined as the available generation capacity over peak demand [258]. As the power system is being decarbonized and increasingly relies on variable renewable energy, it is no longer possible to assume that generation capacity is relatively constant. For this reason, in recent years, the methodologies for estimating adequacy have evolved from a deterministic to a probabilistic approach.

In Europe, a new methodology called the European Resource Adequacy Assessment (ERAA) was introduced in accordance with Article 23 of the Regulation (EUR) 2019/943 of the European Parliament and of the council on the internal market for electricity [21]. This replaces the Mid-term Adequacy Forecast (MAF), which does not meet the requirements of the Clean Energy Package. The regulation specifies that resource adequacy assessments should contain scenarios with different likelihoods, such as extreme weather scenarios due to climate change. In addition, interconnection targets, energy efficiency, sector integration and carbon price developments should be considered in the scenarios [259].

The ERAA specifies that the reliability standard should be expressed either in terms of Loss of Load Expectation (LOLE) or of Expected Energy Not Served (EENS)[260]. The LOLE is the expected number of hours per year (h/y) during which load needs to be shed. This is a common reliability standard; the accepted values are normally between 3 and 8 hours per year [261]. The EENS is the expected volume of energy (GWh/y) that the system will not be able to supply [257]. The ERAA also requires the likelihood of changes in the capacity mix to be considered through an economic viability assessment (EVA). The EVA has two steps. In the first step, the least-cost generation portfolio is established through a Monte Carlo probabilistic analysis. The second step is an iterative process in which the results from the previous step are validated by identifying which assets would be likely to be invested in and which ones would be decommissioned [259, 262].

A.4. THE ROLE OF FLEXIBILITY IN FUTURE ELECTRICITY MARKETS

Flexibility has been widely recognized as a key enabler for the integration of a high share of variable renewable energy sources. Currently, system flexibility is mainly provided by fossil fuel plants. They can be replaced in part by other thermal plants, for instance, that are fueled by biomass or hydrogen, but these will be much more expensive. Energy storage units will also contribute to flexibility, but storage units that provide back-up power and therefore do not charge and discharge frequently will have high costs per cycle. Moreover, demand response will contribute to system adequacy by shifting demand from shortage periods to other times. Demand response can be enhanced by sector coupling, e.g. electrification of transport, industry and space heating.

As the system becomes more flexible, the dynamics of the electricity market will change. At times of abundant variable renewable energy supply, storage units and price-responsive demand will increase their consumption, avoiding the near-to-zero or even negative prices. This situation will lead to a longer demand curve with a gentle slope (see Fig A.1). When supply is scarce and the electricity price is set by the high cost of flexible generation, consumers will bid up against each other. Consumers with a lower willingness to pay—facilitated by smart appliances and digitalization—may choose to reduce their consumption or shift it to another moment. At the times when the price is high enough, storage units will also start to produce electricity A.1. Both demand response and storage will dampen the prices. A generation shortage may not necessarily lead to outages, but manifest itself through price spikes.

As the power mix becomes decarbonized, the technologies, the regulation, the players in the market and the resulting electricity prices will evolve continuously. Currently, very high prices near the value of lost load (VOLL) are rarely, if ever, seen in the European electricity markets[263, 264]. As the increase of variable renewable energy sources gradually reduces the operating hours of thermal plants, these units will become increasingly dependent on such high price spikes to recover their fixed costs. Similarly, the business cases of low-carbon generation and of energy storage units, which operate less frequently than on a day–night schedule, will also rely on price spikes. On the other hand, the demand for these expensive resources can be reduced by consumers' willingness to shift load.

The current European reliability standards are calculated with a single VOLL. Ovaere et al. [265] suggest differentiating the VOLL per consumer group, interruption time and other aspects. They demonstrate that prioritizing the reliability of supply based on a differentiated VOLL, instead of a single one, can reduce operational cost by 2–18 % in a 118-node network. However, in a consumer centric power system, price responsive demand is likely to increase. Consumers ideally would indicate their willingness to pay themselves and reduce or shift load if the price is too high. As a result, we share with Swinand et al. [266] the conclusion that the VOLL will become less relevant in future energy systems.

A.5. SHORTCOMINGS OF CURRENT ADEQUACY INDICATORS FOR FUTURE POWER SYSTEMS

Demand flexibility comes at a cost in terms of convenience to household consumers and in lost productivity in case of commercial consumers. Thus, a trade-off will need to be made between investing in flexible generation and storage on the one hand and demand elasticity on the other. Welfare maximization entails optimizing this trade-off; it is the objective of market design to let the market provide the correct signals to all market participants. Although the EVA considers economic aspects in its adequacy assessment, it states that the optimal capacity volume can be estimated through a cost minimization analysis. This approach was valid in a situation without demand response, but it falls short in the presence of consumer price elasticity. In the presence of demand response, the objective is no longer to minimize the cost of power supply, but to maximize overall welfare, taking into account the cost of flexibility to consumers.

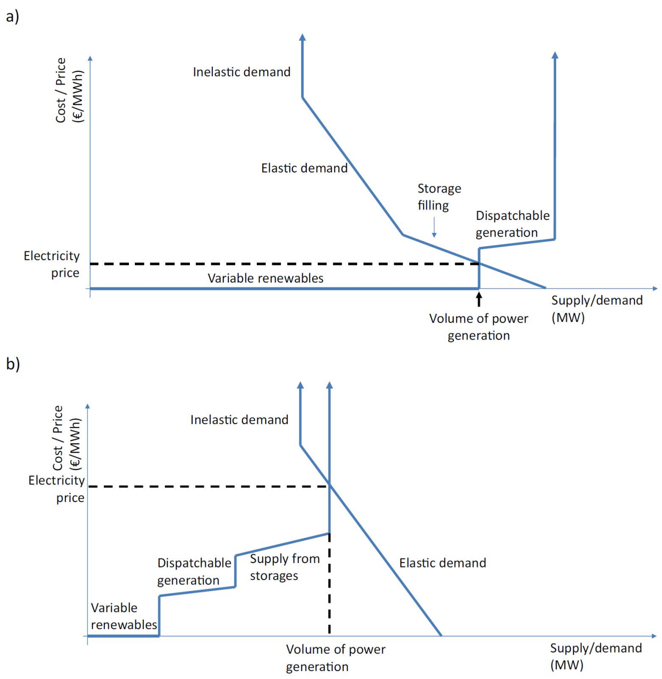

Figure A.1: Future supply and demand curves with increased flexibility at times of (a) abundant variable renewable energy and (b) limited variable renewable energy.

Despite consumer demand elasticity, the cost of dispatchable generation and backup storage facilities may be so high that peak prices may be inevitable for recovering their costs. Hence, a certain volume of high prices will be normal. Consequently, the future power system will be characterized by volatile electricity prices, despite the increase in flexibility. In these new price dynamics, a lack of system adequacy—a shortage of dispatchable generation and storage, considering the available demand elasticity—may not necessarily lead to power interruptions. Instead, a lack of adequacy could manifest itself in prolonged periods of high prices, which would cause excess demand reductions, more than the optimal level from a socio-economic perspective. If average prices rise well above the average cost of power supply, this may indicate a lack of investments in the power system, even if the market demand can be covered by supply. In this case, the current indicators of system adequacy no longer suffice, as they only measure physical shortages.

A second respect in which the ERAA needs to be made future-proof is in theway in whichweather uncertainty is handled. While the method considers the general effects of climate change in its scenarios, the real stress test of a future power system will arise during a prolonged combination of adverse weather conditions. For instance in northern climates, a cloudy, cold and windlessweather period, with low energy supply and high demand, will be the main challenge. There will be a range of such events, with the larger (more adverse) ones being less likely. But society will become more reliant on electricity and may still want to protect itself against these events, even if they occur not more than once in 20 years. This raises questions of how adequacy will be provided during rare, extreme weather events and how to measure the ability of the energy system to withstand such events in the future.

A.6. MARKET SIGNALS AS ADDITIONAL ADEQUACY INDICATORS

In the Texas blackout of 2021, electricity prices were allowed to rise to 9000 $/MWh; total electricity bills for the shortage period added up to an estimated $47 billion [82]. Although the Texas blackout was not due to a lack of installed capacity, this illustrates how blackouts are not only a matter of unserved energy, but may also produce large income transfers. If average electricity prices are above the average cost of power supply, this would imply windfall profits to generation companies. The opposite case could imply that there might not be enough incentives to invest and that the security of supply is in danger. The EVA recognized that it is essential to consider the cost recovery of investments, remarking that the revenues should be equal to the costs. In this sense, the EVA accepts that the cost recovery level is an indicator of system adequacy, but its focus is on revenue sufficiency. However, the other side, excess revenues, should also be considered. Perez-Arriaga et al. [267] argued that in systems with significant elasticity of demand, prolonged or frequent periods of high electricity prices can be a supplementary indicator of system stress, in addition to the traditional measures of outage risk.

Flexibility will be an intrinsic aspect of system adequacy in the future; price volatility is an indicator of it, in the sense that high volatility indicates low flexibility [268]. Price volatility implicitly includes many effects; for instance, negative power prices suggest limited ramp-down capabilities, while price spikes indicate shortages. Dozens of technical parameters influence a system's flexibility, and some have countervailing effects on price volatility. Price volatility indicates their net effect on the system. A concern is, however, that market signals in the form of high price spikes might be less socially acceptable than a certain volume of outages, and might therefore lead to regulatory intervention [269]. Moreover, volatile prices increase investment risk and therefore capital cost. Hence, price volatility may also be considered as an indicator of system performance and an early signal of stress in the system.

Future market design should provide a reasonable level of cost recovery at a reasonable risk to investors. Otherwise, underinvestment may lead to average electricity prices well in excess of the average cost of power supply, if not to periods of outages. Price volatility should be dampened with economically efficient flexibility measures, but should not be suppressed, as short-term prices provide a key operational signal to all market parties. Changes in market design such as implementing a capacity market or capacity subscription may dampen price volatility and improve adequacy, even in a low-carbon electricity system [170]. To effectively judge the (expected) performance of new market designs, cost recovery and price volatility need to be added to the set of adequacy indicators.

A.7. CONCLUSIONS

Adequacy indicators were developed at a time when demand response was limited. Historically, their purpose was to signal whether supply could meet demand. Current adequacy indicators are still based on outage rates and the value of lost load. In a future power system, in which consumers exhibit significant flexibility and thereby avoid (a large share of) physical shortages, these standards are insufficient as indicators of the level of stress in the system. System stress can also be expressed through higher price volatility and excessive prices without physical outages. We propose to add market signals based on the degree of cost recovery and price volatility as indicators of system adequacy.

B

Co-simulation EMLabpy - COMPETES

In the initial stage of the project, we attempted to co-simulate COMPETES with EMLabpy. COMPETES is an optimization model developed by TNO and used by the Dutch government in the country's Energy and Climate Plans [228]. COMPETES can be executed to optimize the dispatch and minimize costs in a capacity expansion with a set of demand and generators, and can simulate sector coupling, cross-border transmission, and multiple flexibilities, in contrast to EMLabpy, which has limited flexibility. Jim Hommes programmed this co-simulation for his master's thesis, and I was very involved in conceptualizing the energy policies, co-simulation, and data exchange. The initial plan was to make a co-simulation where the investment decisions were executed in EMLab based on dispatch results from COMPETES. In this way, we could resemble investment decisions with myopic behavior, while the dispatch decisions would include many flexibility types. EMLab is a standalone model programmed in Java. To develop a co-simulation, it would have been necessary to rewrite most of it in a modular way. So we decided to program from scratch a Python version of EMLab, which we call EMLabpy.

The co-simulation of EMLabpy and COMPETES was unfeasible for two reasons. First, ABM required power plants to be represented as objects. This would require aggregating the installed capacities repeatedly to import them to COMPETES and then disaggregating them to simulate power plants as objects in EMLabpy. Moreover, we mainly dropped this attempt due to the very long computational times. The investment algorithm of EMLab required an iterative market clearing, and this process was around one hour in COMPETES. Each simulation year required around 20 iterations of investment decisions, each based on dispatch results. Each required around an hour, exponentially increasing the runtime to more than 24 hours, which was unfeasible. After this initial attempt, I then developed a co-simulation between EMLabpy and AMIRIS. This co-simulation is explained in Chapter 2

Jim Hommes [270] programmed EMLabpy and COMPETES soft-linking, executing investment and dispatch decisions in COMPETES and modeling the capacity and CO_2

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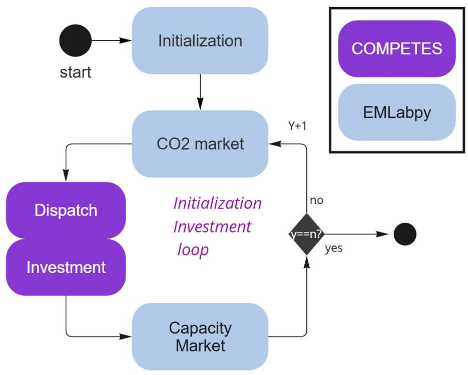

Figure B.1: Workflow of EMLabpy and COMPETES

market in an early version of EMLabpy. The soft-linking was more challenging than expected due to the different ontologies, data structures, units, and programming languages, necessitating additional steps. Nevertheless, it provided valuable insights for the next co-simulation, such as the best practice of minimizing the amount of data stored in the database to speed up the simulations. Moreover, for the next co-simulation, I could recycle many elements of EMLabpy, which was conceptualized in a modular way, including the wrapper functions in which the reader/writer handles the data transfer between the SpineDB and EMLabpy.

In this soft linkage, the CO_2 market was based on the dispatch results of COMPETES and an assumed yearly price cap for NL. The CO_2 price was extrapolated to make future investment decisions based on a future expected CO_2 price. The investment decisions were made 7 years ahead, corresponding to the longest lead time of all technologies. And generators became operational after their lead time. This was achieved by adding a "status" variable in the DB. In a capacity market, the bids were calculated from the missing money, which was computed with the marginal costs, market revenues (from COMPETES), and fixed costs. The capacity market price was modeled in COMPETES investment module as a variable cost reduction, and if the costs reach 0, then a capital cost reduction. This cost reduction was implemented by technology, which then implied that all new power plants accounted for lower costs. To simulate that some power plants in a specific node could receive CRM payments while others don't (i.e., if the CM auction was full), then it would have required adding more classifications of technologies (with and without CRM). For more details, refer to his master's thesis [270].

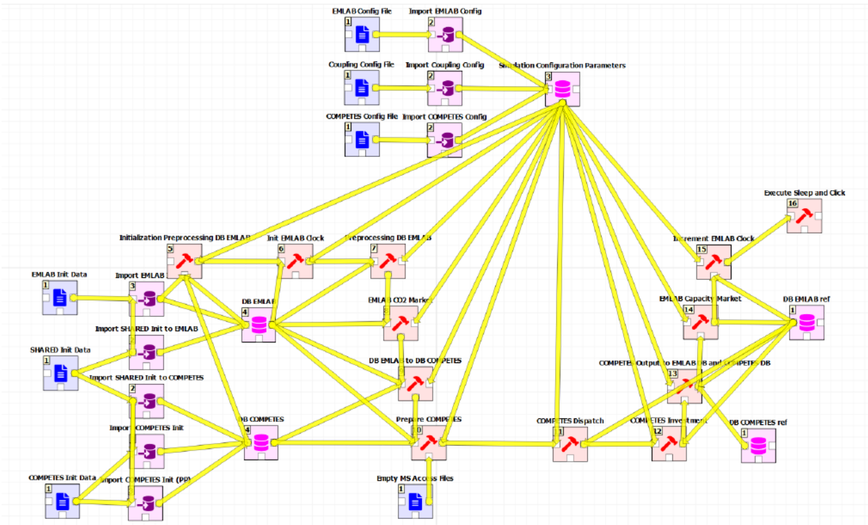

Figure B.2: Workflow of EMLabpy and COMPETES in the Spinetoolbox developed by Hommes [270]

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List of Publications

1. **I. Sanchez Jimenez**, D. Ribo-Perez, M. Cvetkovic, J. Kochems, C. Schimeczek, L. de Vries *Can an energy-only market enable resource adequacy in a decarbonized power system? A co-simulation with two agent-based-models*, Applied Energy **360**, (2024).

2. **I. Sanchez Jimenez**, K. Bruninx, L. de Vries. *Capacity Remuneration Mechanisms for Decarbonized Power Systems*, Applied Energy **391**, (2025).

3. **I. Sanchez Jimenez**, S. Johanndeiter, L. de Vries. *Capacity Remuneration Mechanisms for Power Systems in Transition*, SSRN (2025).

Other Publications

1. L. de Vries **I. Sanchez Jimenez**, *Market signals as adequacy indicators for future flexible power systems*, Oxford Open Energy **1**, (2022).

List of Conferences

1. **I. Sanchez Jimenez**, L. de Vries. Can an Energy Only Market (EOM) enable Resource Adequacy in a nearly 100% Renewable Power System? 13. Internationale Energiewirtschaftstagung an der TU Wien. February 2023. Vienna, Austria

2. **I. Sanchez Jimenez**, L. de Vries. EMLabpy. Agent-Based Modeling for Energy Economics and Energy Policy. February 2023. Stuttgart, Germany

3. **I. Sanchez Jimenez**. M. Cvetkovic, L. de Vries. Coupling AMIRIS and EMLabpy. 19th International Conference on European Energy Markets. TradeRES special session. June 2023, Lappeenranta, Finland

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5. **I. Sanchez Jimenez**, L. de Vries. Capacity Mechanisms in a Decarbonized Power System. Agent-Based Modeling for Energy Economics and Energy Policy. March 2024. Freiburg, Germany

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