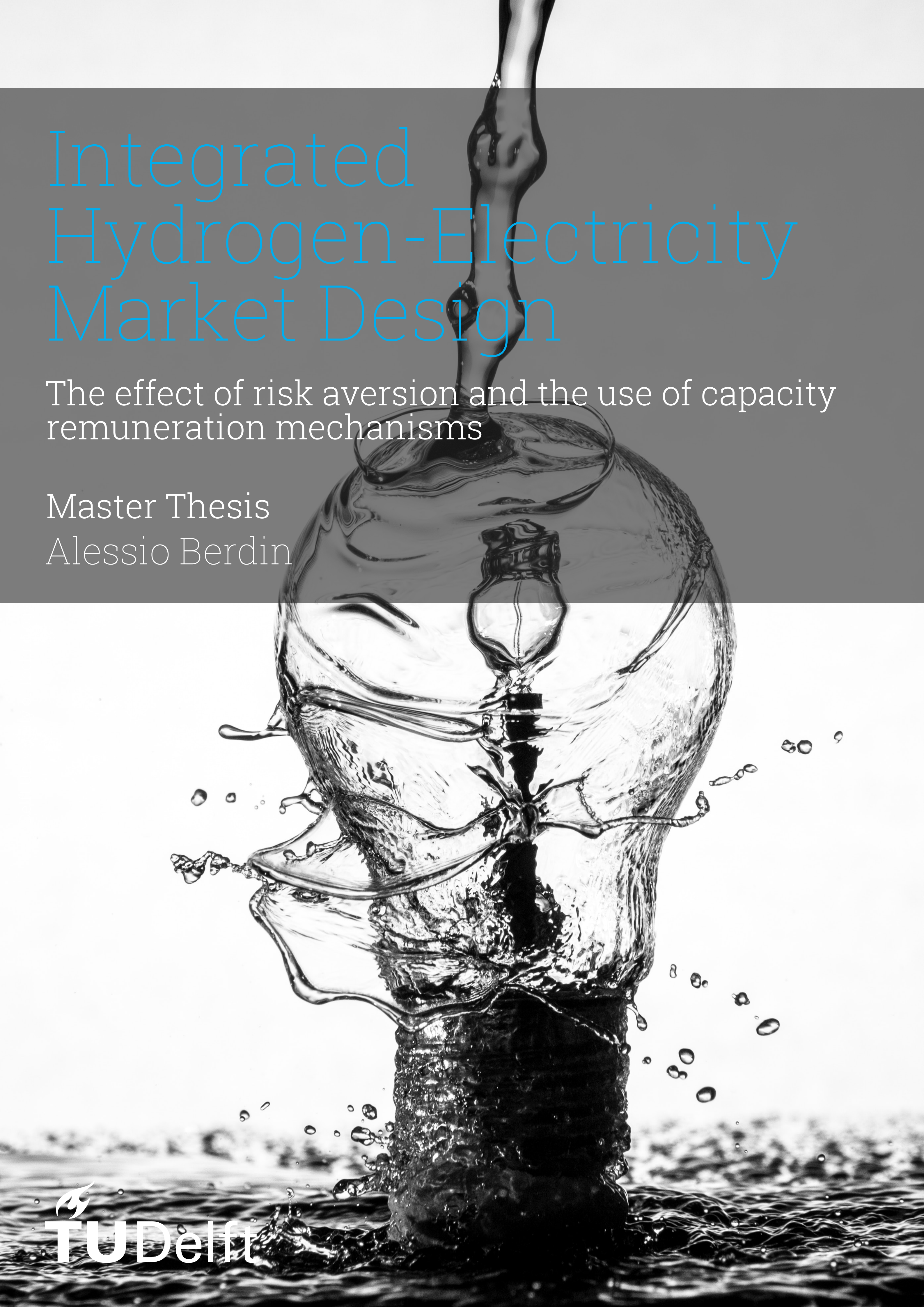

Integrated Hydrogen-Electricity Market Design

The effect of risk aversion and the use of capacity remuneration mechanisms

Master Thesis

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Integrated Hydrogen-Electricity Market Design

The effect of risk aversion and the use of capacity remuneration mechanisms

by

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Summary

The decarbonization of the energy system is driven by the electrification process and the expansion of variable renewable energy capacity. Green hydrogen, produced through electrolysis powered with renewable electricity, represents a major complementary vector that can support this transition. By enabling long-term storage, it addresses the challenges arising from the unpredictability of a renewable energy-based electricity system. It represents a backup and increases the reliability of the electricity system.

However, in an interconnected decarbonized system where energy carriers are interdependent, new sector-coupling dynamics emerge. Energy-only markets, in theory, yield socially optimal levels of installed capacity across both sectors assuming rational participants and perfect markets. However, risk-averse behaviour among market participants might lead to underinvestment in generation capacity, undermining the efficacy of hydrogen backup.

The main objective of this research is to assess the adequacy of market designs in attracting socially optimal levels of investment in electrolyzers and storage capacity within a decarbonized and integrated system with risk-averse agents.

The research is conducted by formulating a stylized stochastic equilibrium model for the integrated energy system and studying the resulting long-term equilibrium solved by using the Alternating Direction Method of Multipliers algorithm. In general, agents participate in an energy-only market, a capacity market for dispatchable electricity generation and a capacity market for hydrogen generation. The demand for electricity and hydrogen is considered price-elastic. Participants formulate their strategy based only on market clearing prices, which are influenced by 18 scenarios which differ in terms of electricity demand, hydrogen demand and variable renewable energy sources availability.

The analysis is conducted by simulating three different market designs (energy-only market, energy market supported by a capacity market for electricity generators, and energy market supported by capacity markets for both electricity and hydrogen generators) under different degrees of risk aversion. The results are compared in terms of investment levels, energy served, average electricity and hydrogen prices, and variation in costs and social welfare.

The analysis confirms how risk aversion, by increasing the risk premium required, entails a reduction in installed capacity with respect to the optimal risk-neutral scenario. This is valid for all the agents apart from the flexible capital-intense generator, as a result of the independence of its availability and variable costs from the considered uncertain parameters, reducing the direct impact of risk aversion. Underinvestment is combined with a general reduction in the served energy and an increase in the energy prices and in the frequency of periods of high prices. These trends are more considerable in the hydrogen market, where agents are exposed to risk from the uncertainties in hydrogen demand and are also strongly influenced by electricity prices, which are uncertain as a consequence of the availability of vRES generators and electricity demand.

Among the various designs, the energy-only market is more sensitive to the impact of risk aversion due to the absence of risk trading opportunities. Therefore, the increase in energy prices is the only solution to recover the risk premium.

Introducing a capacity market for dispatchable electricity generators mitigates the impact of risk aversion in the electricity sector. However, this enhancement does not extend to the hydrogen sector; instead, it exacerbates performance issues during scarcity periods by amplifying hydrogen price fluctuations. On the other hand, incorporating a capacity market for hydrogen as well effectively counteracts the effects of risk aversion on the hydrogen sector. This dual approach not only benefits the hydrogen

sector but improves the electricity sector's adequacy and reduces consumer costs.

From this thesis, it can be concluded that risk aversion significantly reduces investment in generation capacity. In a hydrogen sector powered by a vRES-based electricity backbone, this impact is amplified due to exposure to risk from electricity prices. Capacity markets are an effective instrument to hedge risk, but their application in an integrated system has to be consistent and include both electricity and hydrogen generation capacity. Furthermore, the strong dependence of hydrogen generation on electricity prices advocates for a direct instrument to mitigate the risk aversion of renewable generators such as contracts for difference, as an adequate vRES capacity improves the whole system's performance by reducing hydrogen prices and increasing its availability.

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Nomenclature

Abbreviations

ADMM	Alternating Direction Method of Multipliers
CfD	Contract for Difference
CM	Capacity Market
CRM	Capacity Remuneration Mechanism
CVAR	Conditional Value at Risk
ENTSO-E	European Network of Transmission System Operators for Electricity
EOM	Energy Only-Market
ERD	Enhanced Representative Days
EU	European Union
IEA	International Energy Agency
KKT	Karush-Kuhn-Tucker
LHV	Lower Heating Value
MCP	Mixed-Complementarity Problem
PPA	Power Purchase Agreement
P2G	Power-to-Gas
PHES	Pumped Hydro Energy Storage
RES	Renewable Energy Sources
vRES	Variable Renewable Energy Sources
WTP	Willingness to Pay

Symbols

Sets

a	Set of agents
ad	Set of days
d	Set of representative days
t	Set of time steps within a day
r	Set of renewable generators
y	Set of scenarios
k	Set of iterations

Symbols

α	Value at Risk (VAR)	M€
β	Risk aversion	-
Π	Profit	M€
Ψ	Percentage of price inelastic demand	-
γ	Weight of expected surplus	-
η	Efficiency	-
$\lambda^{e}_{dt,y}$	Electricity price	€/MWh
$\lambda^{H_2}_{dt,y}$	Hydrogen price	€/MWh
$\lambda^{CM,e}$	Electricity capacity price	M€/GW
λ^{CM,H_2}	Hydrogen capacity price	M€/GW
Δh	Net daily storage energy exchange	MWh
ρ	Penalty parameter	-
A	Availability factor	-
IC	Investment costs	M€/GW
IC_P	Investment costs for storage capacity	M€/GW
IC_V	Investment costs for storage volume	€/MWh
cap	Installed capacity	GW
$cap^C M$	Capacity contracted in the capacity market	GW
ch	Hydrogen charge	MWh
$D_{CM,e}$	Demand for electricity generation capacity	GW
D_{CM,H_2}	Demand for hydrogen generation capacity	GW
D^e	Reference electricity demand	MWh
D^e_{ela}	Maximum share of price-elastic electricity demand	MWh
D^{H_2}	Reference hydrogen demand	MWh
$D^{H_2}_{ela}$	Maximum share of price-elastic hydrogen demand	MWh
dh	Hydrogen discharge	MWh
e	Electricity generated	MWh
e^{WTP}	Inelastic electricity consumption	MWh
e^{ela}	Elastic electricity consumption	MWh
h	Hydrogen generated	MWh
h^{WTP}	Inelastic hydrogen consumption	MWh
h^{ela}	Elastic hydrogen consumption	MWh
n	Lifetime	y
OC	Overnight Costs	M€/GW
P	Storage installed capacity	GW
P_y	Probability of scenario y	-
r	Discount rate	-
SOC	State of charge	MWh
SOC^0	Initial state of charge of the day	MWh
V	Storage volume	MWh
$V_{ad,d}$	Ordering matrix of representative days	-
VC	Variable operational costs	€/MWh
W	Weight of timestep	h
WTP	Willingness to pay	€/MWh
u	Profit difference with VAR	M€

1
Introduction

Climate change is one of the biggest challenges that human beings have ever faced, with devastating effects on the biosphere, and on human beings as part of it. The awareness of human responsibilities for global warming and the necessity of taking strong initiatives to mitigate its consequences are reflected in the progressive iterations of the Intergovernmental Panel of Climate Change reports. Many countries have adopted the Paris Agreement to accelerate the deployment of low-carbon technologies to limit the temperature increase to 1.5 degrees Celsius with respect to pre-industrial levels and undertake the energy transition as one of the pillars to tackle this environmental challenge. At the same time, decarbonizing the energy system means safeguarding the environment while providing opportunities for socio-economic development, guaranteeing the possibility for sustainable development (Vanegas Cantarero, 2020). For these reasons, climate actions are at the top of public agendas, and the decarbonization of the energy system with it.

A powerful instrument to reduce emissions from the energy sector is identified in electrification and the simultaneous expansion of renewable energy sources (RES) generation capacity. Under the announced ambitions and targets, by 2050 electricity demand is likely to grow by 120% with respect to the 2021 levels to represent up to 40% of global final energy consumption, and the renewable share is expected to increase from 28% to 80% (IEA, 2022). However, because of their intermittent and unpredictable availability, the increasing share of variable renewable energy sources (vRES) in the electricity mix challenges the picture of the power system, both in operational and market dynamics.

In the short term, vRES intermittency affects the real-time power balance and increases the demand for flexibility. At the same time, these energy sources are associated with near zero-marginal costs. These two features of vRES electricity are reflected in the market by increasing volatility and putting downward pressure on electricity prices, which in turn increase investment risk (Li & Mulder, 2021; Keppler et al., 2022). Looking at a longer time frame, vRES generation presents seasonal patterns and is subject to extreme events of prolonged cold, dark periods without wind (referred to as *dunkelflauten*), which trigger the need for long-term storage (Blanco & Faaij, 2018).

Alongside electricity, hydrogen could represent a major complementary actor in a low-carbon economy (Staffell et al., 2019). Thanks to its versatility of applications, both in the electricity sector and with industrial purposes, hydrogen is gaining momentum in the world energy market and, strengthened by the current energy crisis provoked by the gas security crises, it is expected to reach up to 10% of total final consumption (IEA, 2022).

Hydrogen long-term storage can improve the energy security of supply and self-sufficiency in a decarbonized energy system (IEA, 2019; Elberry et al., 2021). When combined with hydrogen-fired turbines, it would provide a backup solution for extreme events such as *dunkelfaluten*, namely long periods of time without wind and sun (Koirala et al., 2021). Unlike battery electricity storage, which is affected by self-discharge and would require an enormous number of batteries, compressed hydrogen storage in salt caverns stand out for high energy capacity and, potentially, relatively low capital costs, which make it the most economical option for discharge durations beyond a day (IEA, 2019; Alvik & Onur Özgün et al., 2022). Furthermore, multiple studies prove how electrolysis hydrogen can provide flexibility to the power system, effectively reducing power curtailment and the amount of energy not served, which in turn reduces price volatility and benefits generators with additional revenues (Li & Mulder, 2021; Hesel et al., 2022; Koirala et al., 2021).

Besides the benefits that it would provide to the power system, green hydrogen is a suitable alternative to the use of fossil fuels in hard-to-abate sectors, for which decarbonization is quite challenging as direct electrification is not possible or convenient. It can be used as a reduction agent in the steel industry, as a key feedstock in many chemical processes, and as a fuel in the shipping and aviation sectors, contributing to significantly reducing emissions of these sectors (IEA, 2019). It is under investigation if hydrogen could play a role in reducing natural gas demand for heating, both by being injected into the existing gas network and directly used for district heating (IEA, 2020).

It is important to mention that, if electrolytic hydrogen can mitigate the drawbacks of vRES, the European Union (EU) proposed strict requirements for electrolytic hydrogen to be defined as renewable or green. Indeed, it must respect the additionality requirement, which results in dedicated additional renewable power capacity specifically built for hydrogen production. Moreover, the latter requires a certain degree of temporal and geographical correlation with the generation of additional renewable-based electricity (Bruninx et al., 2022).

The hydrogen scale-up faces different barriers, such as high capital costs (Roach & Meeus, 2020; van Leeuwen & Mulder, 2018), limited enabling infrastructure (Staffell et al., 2019) and large energy losses from production to consumption (IEA, 2019). However, the political determination of the EU to develop and use hydrogen is driving the sector's growth, and reliable long-term demand for low-emissions hydrogen will be the main driver of investment for scaling up (IEA, 2022). In 2018, hydrogen made up only 2% of the energy mix in Europe, and 96% of it was produced from fossil-based technologies or as an industrial by-product (European Commission, 2020). However, given the urgency of the energy transition and potential technological development, the EU is working towards creating an EU-wide decarbonized hydrogen backbone with a focus on upscaling hydrogen production. The priority is on renewable hydrogen obtained from electrolyzers powered by RES, as it aligns with climate neutrality and systems integration goals (European Commission, 2020). The REPowerEU plan aims to achieve 10 million tonnes of domestic renewable hydrogen production and 10 million tonnes of renewable hydrogen imports by 2030, with 40 GW of electrolyzer capacity installed (European Commission, 2022). By 2050, it is expected that renewable hydrogen technologies will be mature and widely deployed, and an open and competitive hydrogen market will exist (European Commission, 2022).

This recent policy boost motivated this work, which focuses indeed on investigating the potential upscaling of a green hydrogen sector and its relation with the electricity sector. The road toward decarbonization is based on the integration of different technologies to ensure an efficient, reliable, and sustainable energy system. The rise of hydrogen as an energy carrier and its inter-dependency to the electricity sector, from which it can be produced and can serve as a support, trigger new sector-coupling dynamics. This results in a complex integrated energy system, with challenges both in the operational layer, where technologies physically interact, and in the market layer, through which the socially optimal outcome must be ensured. This thesis focuses on the latter, and in particular how integrated energy market designs can provide the required price signals for adequate investments in generation and storage capacity across energy vectors.

Investment in generation capacity is in general justified by recovering costs based on expected returns from the markets. This means that investors are prone to install additional capacity as long as they are sure that they will be remunerated adequately during the lifetime of the asset. In theory, energy-only markets (EOM) - which only remunerate the energy sold - can provide adequate price signals during scarcity periods which allows investors to recover their costs, attracting the optimal level of investment and technology mix (Joskow, 2008). However, as experienced in electricity markets, the socially optimal outcome can be distorted in reality, due to different factors which undermine the essential assumptions of perfect competitive electricity markets. Among others, these factors are the absence of a price-elastic demand, the presence of price caps, strategic behaving investors, imperfect information, and, finally, risk-averse investors (Kaminski, 2022). These factors have in common that they potentially lead to the so-called "missing money problem", for which price signals of EOMs are not high and frequent enough to incentivize investment in the optimal capacity (Joskow, 2008). The current increasing share of VRES-electricity constrains the merit order to even lower and more volatile prices, exacerbating the "missing money" problem (Newbery et al., 2018; Keppler et al., 2022). The distortion of the market resulting from the lack of investment ultimately leads to a lack of reliability, with important consequences on society (Kaminski, 2022).

Among others, risk aversion plays a crucial role in determining investments, due to spot-prices uncertainty and the capital-intensive nature and long payback periods of generation assets (De Vries, 2007). Imperfect information about future revenues and, in general, market conditions could indeed lead investors to postpone, lower and even discard a potential investment. Instruments to hedge risk are various, but uncertainties in terms of regulations, demand, and technology prices combined with long-term payback periods make the energy market incomplete, i.e. risk can be traded only partially with financial instruments and market design choices (De Maere d'Aertrycke et al., 2017).

A widely recognized possible solution to mitigate capacity scarcity has been identified as capacity remuneration mechanisms (De Vries, 2007). These instruments propose to remunerate generators for the installed capacity on top of the revenues earned on the energy market. From real-world experiences, capacity mechanisms have been a successful instrument to ensure power generation adequacy across the world, and in general, they can efficiently coexist with renewable energy support policies (Kozlova & Overland, 2022). An overview of the influences of real-world factors and potential market corrections that influence energy markets' outcomes is presented in Figure 1.1.

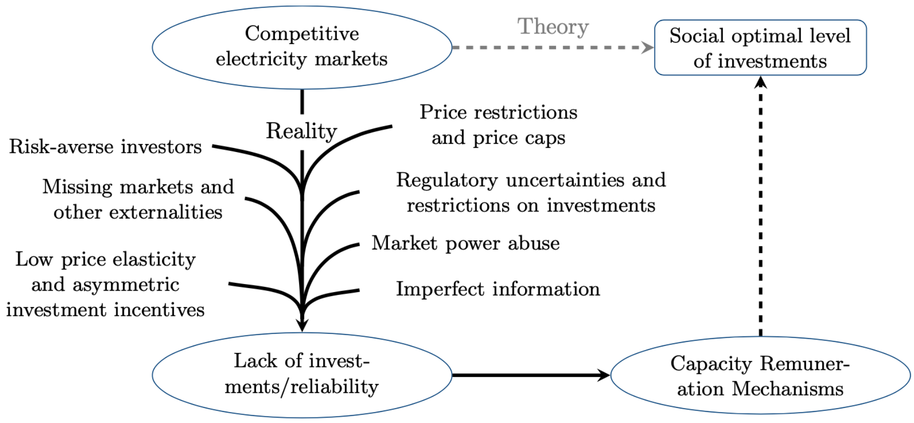


Figure 1.1: Energy markets in theory vs. reality (Kaminski, 2022)

The potential scale-up of the hydrogen sector needs a careful investigation of the experience in electricity markets, but it must be also based on the new dependencies that are triggered. Indeed, the cornerstone of the integrated electricity-hydrogen market lies in the sector-coupling agents and in the circular dependency at its base.

A potential electricity sector fully based on RES electricity and with a long-term hydrogen storage backup would rely on hydrogen turbines to cover the residual load, therefore requiring a certain degree of hydrogen availability. However, as electrolysis is expected to become the main form of hydrogen generation, the availability of electricity generation capacity is crucial and in turn makes hydrogen availability dependent on volatile vRES. Long-term storage plays therefore a fundamental role in decoupling the generation and consumption of hydrogen; however, the interdependencies of the two sectors and the unpredictability of a decarbonized system based on vRES create issues in managing and valuing long-term storage. The latter must be available to provide backup even during rare, extreme weather events of cold, prolonged periods without wind and sun, which can happen up to once every 20 years. These will be the real stress test of future power systems, and with a society increasingly reliant on electricity, it might want to protect itself against those events (De Vries & Sanchez Jimenez, 2022).

The increased reliability that the last units provide to the integrated system has a high intrinsic value, which in EOMs is remunerated accordingly by scarcity prices. In this context, scarcity prices of hydrogen could affect the electricity market, with a general transposition of flexibility issues (Vandewalle et al., 2015). However, considering weather uncertainty and the rarity of events which require the full capacity and volume of storage combined with capital-intensive investment, it is clear how risk aversion could play an important role in orienting the market performance. Scarcity periods and the consequent price signals could not be enough to convince risk-averse investors and the resulting underinvestment would undermine the effectiveness of long-term storage and the related assets. On the other hand, remunerating hydrogen capacity could only partially solve the problem, given the availability is dependent on other assets, i.e. vRES electricity generators.

To derisk investment in the hydrogen sector and ramp up the hydrogen market, the EU proposed a funding scheme via the European Hydrogen Bank (European Commission, 2023). Similarly, the German H2Global Foundation launched the first combination of long-term Hydrogen Purchase Agreements with Hydrogen Sales Agreements to reduce the uncertainty on both the supply and demand sides and drive the reduction of costs for green hydrogen. However, these market-based solutions focus on electrolysis and do not address the remuneration for hydrogen storage and hydrogen turbines for backup.

Sectors coupling interdependencies blend responsibilities for the integrated system availability and create issues in valuing the different technologies and their operation. The efficient integration of hydrogen into the energy system is therefore challenging.

1.1. Research Gap

Integrated hydrogen and electricity systems started to be investigated recently to understand what could be the long-term equilibrium and what implications this sector-coupling could entail.

Multiple studies affirm how Power-to-Gas (P2G) via electrolysis is correlated with increasing integration of vRES, in particular wind energy (Green et al. (2011); Lynch et al. (2018); Lux & Pfluger (2020); Hesel et al. (2022)). In particular, P2G is beneficial in the context of high renewable energy share thanks to the flexibility it can provide to the power system (Vandewalle et al. (2015); Li & Mulder (2021); Hesel et al. (2022)). The large demand for electricity coming from the electrolyzers would increase the installed power capacity, and at the same time, it would benefit renewable generators by reducing zero-price periods (Hesel et al., 2022). However, flexibility comes with a cost and not always the beneficial effects for the electricity and hydrogen sectors are aligned. Based on the current costs of electrolyzers, P2G is not yet a competitive technology itself and often comes with a negative economic value. This conclusion has been reached from the application of both optimization models (Hesel et al. (2022); Lux & Pfluger (2020)) and equilibrium models (Li & Mulder (2021); Roach & Meeus (2020); Lynch et al. (2018)). Additionally, Vandewalle et al. (2015) explain how flexibility issues of vRES are partially transposed to the gas sector and the system increases in complexity.

Due to the recent interest in the integrated hydrogen-electricity market, the results are mainly characterized by a general approach to investigate the effects of such integration rather than considering possible market distortions led by risk aversion. On the other hand, risk aversion is a concept widely modelled and analyzed in electricity markets since their liberalization. It has been recognized how the combination of risk aversion and typical features of the energy market such as the long-term capital-intensive nature of investments, price volatility and incomplete information can reduce and postpone investments in new capacity (De Vries, 2004). Among the first who tried to address the resulting underinvestment problem, Neuhoff & De Vries (2004) proposed CRMs as a possible solution to mitigate the distortions caused by risk aversion. Among the recent studies which debate risk and market corrections, equilibrium models are widely used as they can effectively represent market participants' behaviour (Ehrenmann & Smeers (2011); De Maere d'Aertrycke et al. (2017); Höschle et al. (2018); Mays et al. (2019); Kaminski et al. (2021)), followed by system-dynamics models, which outcomes are driven by causal relations implemented by using feedback loop adaptation of the strategies (Petitet et al. (2017); Ousman Abani et al. (2018)). In general, they all agree on how EOMs for electricity are very sensitive to risk, and how they are outperformed by capacity markets in terms of ensuring electricity generation adequacy.

By definition, capacity markets and, more in general, capacity remuneration mechanisms intend to remunerate generation capacity on top of revenues from the wholesale energy market. However, their goal to ensure generation adequacy can be additionally supported by different solutions such as demand flexibility and energy storage (Fraunholz et al., 2021). Focusing on storage, there are different studies which try to assess the effect of allowing electricity storage participation in CRMs (Askeland et al., 2019; Schmitz et al., 2013; Fraunholz et al., 2021). Schmitz et al. (2013) affirm that pumped hydro energy storage (PHES) inclusion in CRMs can be beneficial for the technology mix efficiency. Askeland et al. (2019) support this conclusion by using a complementary model, highlighting how investments in PHES and battery energy storage are stimulated by a capacity market and reduce at the same time the need for conventional thermal power plants. However, Fraunholz et al. (2021) explain how the functioning of CRMs precludes a straightforward inclusion of energy storage technologies. They indicate the specification of who bears the risk of empty storage and the derating of storage availability as the main bottlenecks for an efficient inclusion in CRMs, finding reliability options based on a trade-off between the strike price and the choice of the derating factors an effective solution to support storage and ensure the security of supply. These works are however focused on electrical storage. Furthermore, Fraunholz et al. (2021), risk aversion is not explicitly modelled, as Fraunholz et al. (2021) try to represent risk by the use of different reliability requirements and their connection with derating technologies.

Considering capacity expansion problems for an integrated electricity and hydrogen system, the effect of risk aversion combined with sector-coupling interdependences triggered by a large deployment of electrolytic hydrogen is still unexplored in the literature. Indeed, the effect of risk and the consequent sub-optimal market outcomes have been extensively studied primarily in electricity markets, for which CRMs have been identified as an efficient solution. The participation of storage in such CRMs is currently gaining interest, but it is still limited to electrical storage. Therefore, literature about the potential creation of a hydrogen market lacks considering the market design requirements that may be needed to ensure socially optimal investments in a risk-averse context.

1.2. Research Questions

From an electricity market perspective, it is clear what is the effect of risk on investment in generation capacity and what are effective interventions to correct market inefficiencies. However, when it comes to integrated and decarbonized electricity and hydrogen systems which rely on long-term hydrogen storage as backup, it is not clear how sector-coupling dynamics effects relate to risk aversion. On one hand, price signals in energy-only markets could not be enough to attract adequate investments. On the other hand, the implications and the effectiveness of CRMs for storage in another energy vector have not been studied yet.

The objectives of the project are therefore to assess the impact of risk aversion on the operation and investment in electrolyzers and long-term storage capacity within an interconnected electricity and hydrogen market. In particular, it aims to elucidate what sector-coupling dependencies arise and are crucial in ensuring a reliable system. Furthermore, this thesis aims to examine the effectiveness of capacity remuneration mechanisms, such as capacity markets, in mitigating risk and addressing deviations from the socially optimal generation mix. The long-term equilibrium of the system, modelled at a Dutch scale, introduces uncertainty by considering different weather conditions and electricity demand across various years and diverse scales of hydrogen demand.

The scope of the thesis can be summarized in the following research question, by means of which the presented literature gap can be addressed:

Which market design is best suited to trigger socially optimal investments in generation and storage capacity in a decarbonized and integrated electricity and hydrogen system with risk-averse agents?

The following three sub-questions can be formulated to disentangle the various aspects of the main research question and structure the work.

1. *How does risk aversion impact the investment in and the operation of electricity generators, electrolyzers, and hydrogen storage in an EOM for electricity and hydrogen?*
2. *How can capacity remuneration mechanisms correct the possible suboptimal amount of investment and generation mix led by risk aversion?*
3. *What sector-coupling dynamics drive investment in a decarbonized and integrated electricity and hydrogen system?*

To answer the research questions, a stylized long-term equilibrium problem will be formulated to assess how different market designs - namely EOMs and capacity markets - coordinate investments and what are the consequences in terms of integrated system adequacy of the resulting capacity mix. By conducting this research, this thesis contributes to the understanding of (a) the impact of risk aversion on investment in generation capacity for an integrated hydrogen and electricity system reliant on renewable energy and (b) the requirements of potential capacity markets needed to ensure system adequacy of such a system.

1.3. Thesis Outline

The thesis is organized as follows. Firstly, Chapter 2 analyses the state-of-art literature about integrated hydrogen and electricity system and explores the modelling of risk aversion and the effect of possible market corrections. Chapter 3 illustrates the research approach and the conceptualization of the model by defining the system studied, composed of the markets and the actors who will take part in it. Chapter 4 introduces the mathematical formalization of the problem and its implementation in Julia, the selected programming language. This chapter also provides a description of the algorithm used to solve the problem and the validation of the model. Chapter 5 presents the assumptions used in the model and the market designs analyzed. The results of the simulations are presented in Chapter 6, which are then contextualized and discussed in Chapter 7. Lastly, Chapter 8 presents the conclusion of the thesis, supported by insights for policy-makers and recommendations for future research. Additionally, a personal reflection on the development of the work is provided in Chapter 9.

2

Literature Review

The current developments of hydrogen are reflected also in literature, where the creation of an integrated hydrogen and electricity system has started to be addressed. In particular, the discussion focuses on the long-term equilibrium and what implications sector coupling would have in terms of socially optimal investment and technology mix and how these would affect market dynamics.

The use of a modelling approach is particularly suitable to investigate the long-term dynamics of energy systems as it allows to simulate the evolution of the system given certain assumptions and conditions. Optimization models are historically widely used for this scope, with different degrees of complexity and spatial and temporal resolutions, as for example it is done by Haas et al. (2018), Lux & Pfluger (2020), Koirala et al. (2021), Ball et al. (2007). In general, such models aim to minimize the total cost of providing energy and result in an investment plan and an operational schedule. However, the central planning perspective implicitly assumes perfect competition and therefore is not suitable to model risk aversion, which is a key factor in influencing the investment.

Equilibrium models reverse the central perspective of optimization and allow to express the interaction of individual decision-making agents in competition. To do so, each agent is modelled by formulating its own utility function and the related optimization problem. It is demonstrated that under particular assumptions, the optimization formulation and the equilibrium formulation of a problem are equivalent (Kaminski, 2022). However, the formulation of equilibrium models allows to deviate from the perfect market conditions and to introduce individual preferences of market participants (Höschle, 2018; Dagoumas & Koltsaklis, 2019).

The hydrogen sector scale-up is modelled with a risk-neutral approach, focusing on capturing the effects of coupling the hydrogen and electricity system. Vandewalle et al. (2015) apply an operational model to investigate the effects of Power-to-Gas (P2G) on coupling the electricity, gas and CO2 sectors, highlighting the additional complexity triggered by sector coupling and how the benefits gained by renewable energy production partially transpose the capacity and flexibility issues to the gas sector. However, investments in P2G facilities are considered exogenously. Li & Mulder (2021) confirm how the flexibility provided by P2G benefits renewable producers by formulating an equilibrium model, but they show how their economic value is negative at the current electrolyzers' costs, and it is worsened when considering a competing industrial hydrogen demand. Roach & Meeus (2020) analyzes potentially misaligned incentives led by P2G between the electricity and gas markets. They study the long-run market equilibrium and affirm that a limited amount of P2G capacity lowers the prices of both markets; however, maximizing social welfare often coincides with a loss-making level of investment in P2G. This conclusion is confirmed by Lynch et al. (2018) in the context of optimal investment portfolios. By formulating a stochastic equilibrium model, they point out how P2G itself is a loss-making technology that becomes attractive with increasing renewable penetration when coupled with investment in wind generation. This also confirms the previous conclusion of Green et al. (2011), which analyse the impact of increasing demand for electricity from hydrogen production on the capacity mix by formulating a long-term equilibrium model for a perfectly competitive electricity market and highlight how electrolyzers stimulate the integration of large amounts of wind energy.

Different studies focus more on generation expansion planning, endogenously determining the optimal hydrogen generation capacity. Ball et al. (2007) investigate the hydrogen infrastructure development for the supply of the transport demand and analyze its relationship with the power sector, focusing on the costs of the resulting technology mix and the impact on emissions reduction. Hesel et al. (2022) integrate hydrogen in a long-term European electricity market and propose a system dynamics investment module alongside the optimization dispatch model to investigate the profitability of green hydrogen and its impact on emissions, showing how both are negative in the short term but will benefit the whole system in the longer period, while by providing flexibility they have a good impact RES profitability and price volatility. Lux & Pfluger (2020) investigate the production potential for electricity-based hydrogen in a decarbonized European energy system trying to develop the hydrogen supply curve based on the willingness to pay for it with an optimization model, highlighting the key role of electrolyzers size, efficiency, and operational flexibility in making it competitive and the additional renewable capacity required.

Social optimal perspectives are often good to set targets, but lack representing real-world dynamics. As discussed, the presence of risk averse-investors is crucial in orienting investments.

Since the electricity market liberalization, questions about risk-averse investors' strategies arose. The numerous risk sources in a liberalized electricity market are likely to reduce and postpone investments in capacity and, as a consequence, reduce the reliability of the system and transfer costs from generators to consumers (De Vries, 2004). To avoid shortage situations and improve generation adequacy, Capacity Remuneration Mechanisms (CRM) have been implemented by remunerating capacity providers on top of their revenues from selling electricity in the wholesale market. CRMs have been proven effective in dampening the influence of risk-averse investors on market developments, even though selecting the best market design to implement is often challenging (Bublitz et al., 2019).

The concept of risk aversion has therefore been modelled and analyzed in several generation expansion studies in the electricity sector, which tried to assess the deviation from the optimal mix that it entails, alongside possible solutions to correct the imperfect outcome. Neuhoff & De Vries (2004) investigate how risk aversion affects investment in generation capacity. They show how typical features of electricity markets (e.g. long-term investment horizon, incomplete information of demand and supply, price volatility) lead risk-averse investors to reduce the volume of generation capacity compared to risk-neutral agents, while risk-averse consumers would require a higher volume. They also highlight how the efficacy of long-term contracts suffers from the high competition of the retail market and propose different CRMs to reduce investment risk.

There are two main categories of models that are widely used in literature to simulate long-term markets including risk aversion: system dynamics models and (stochastic) equilibrium models.

System dynamics models are focused on modelling the interactions between the agents of a complex system. By using feedback loops to represent these causal relationships, it is possible to determine the decision rules which drive the system development (Höschle, 2018). In the context of power markets, system dynamics models are used, e.g., by Petitet et al. (2017) and Ousman Abani et al. (2018). Petitet et al. (2017) analyze the impact of risk on different market designs in the context of demand stagnation and an exogenous increase of renewables. They observe how an energy-only market with a price cap does not ensure an adequate level of security of supply, while an energy-only market with scarcity pricing is very sensitive to the presence of risk. Ousman Abani et al. (2018) analyze the effect of risk aversion (accounted through CVAR) on the performance of CRMs in a context with an uncertain peak load. They study an EOM, a capacity market, and a strategic reserve mechanism. They highlight the importance of price caps and the maximum amount of strategic reserve as important design parameters to ensure the efficacy of the CRMs. Both studies confirm that, when a capacity market is well designed, it can reliably enhance the security of supply without being affected by risk aversion.

On the other hand, equilibrium models express the interaction of the agents by representing the individual decision strategies of the participants, allowing them to deviate from the perfect market conditions. Stochastic equilibrium models are widely used as they allow the inclusion of risk aversion in different agents' strategies in a competitive market. Ehrenmann & Smeers (2011) study an EOM and an energy market completed by a capacity market, finding that low price caps deeply affect the performance of an EOM, leading to underinvestment and a deteriorated security of supply, and that a capacity market can correct this market failure. They observe that ensuring generation adequacy by the addition of the capacity market results in higher consumer costs and a technological shift towards less capital-intensive technologies. Also De Maere d'Aertrycke et al. (2017), starting from an EOM affected by a price cap and risk aversion, formulate the different markets design and liquidity levels as stochastic equilibrium problems. They conclude that long-term contracts for difference and reliability options are quite effective complements of EOM when the volumes of trading are high enough, but a lack of liquidity and regulatory limits imposed on physical capacity, respectively, degrade their efficiency. On the other hand, forward capacity markets can enhance welfare and investment without trading risk with customers but determining the optimal demand for capacity can be difficult and their efficacy is heavily dependent on the setting of this target.

Höschle et al. (2018) propose the Alternating Direction Method of Multipliers (ADMM) for large-scale market equilibrium models with risk-averse generation investments. They apply it to a case study and find that, in the presence of risk aversion, a capacity market still provides sufficient investment signals and outperforms an EOM both in terms of total costs and levels of energy not served, even when the price cap of the EOM is increased. Mays et al. (2019), basing their work on Ehrenmann & Smeers (2011) and applying the ADMM method, study capacity markets and the effects of risk trading within incomplete markets. They highlight how achieving an efficient technology mix requires the ability to share risk and how the design of risk-trading solutions as contracts affects the technology mix and usually entails a bias toward a particular technology. They also confirm that current capacity markets have a stronger impact on technologies with higher operating (variable) costs, as they benefit more from the capacity payments out of the infrequent EOM scarcity prices, and in general shift the technology mix toward these peak units. Kaminski et al. (2021) confirm that the inclusion of a capacity market performs better than an EOM against capacity shortages due to risk aversion, enhancing generation adequacy, resulting however in a shift of the technology mix towards low investment costs technologies. Furthermore, considering short-term demand elasticity, they point out how it amplifies the negative effects of risk in reducing social welfare. Capacity markets appear more efficient in mitigating this effect and in dampening the social welfare transfer from consumers to generators.

All these studies, regardless of the method used, investigate the impact of risk on electricity markets but do not consider how a hydrogen sector interconnected to the electricity backbone could change this picture, introducing additional complexity and new sector-coupling dynamics.

Recently, with an increasingly important role of storage technologies in the technology mix, their inclusion in the market support and dynamics started to be analyzed to investigate policy adequacy and storage impact. Askeland et al. (2019) develop a complementary model of the power system to assess the potential of pumped hydro energy storage (PHES) and lead-acid batteries under EOM and energy and capacity market, finding that PHES and batteries are complementary technologies that can reduce the need of conventional thermal power plants. They notice that investments in storage assets are more stimulated by the addition of a capacity market because the latter decreases the uncertainty of cost recovery for storage. Schmitz et al. (2013) show how the inclusion of pumped hydro storage in the CRM benefits the efficiency of the technology mix and, consequently, improves social welfare. They qualitatively discuss different market design parameters that influence storage compatibility with CRM, highlighting the stable long-term horizon of the contracts and technology-specific availability measurement as important drivers of inclusion. Fraunholz et al. (2021) provide a theoretical discussion supported by an agent-based electricity market model to assess how the design of CRMs, with a transparent specification of who bears the risk of empty storage, and the choice of the storage derating factor can influence the competitiveness of electricity storage units and the long-term generation adequacy with respect to an EOM. They highlight that bundling capacity auctions with call options, in this case, reliability options with a strike price, and a well-calibrated setting of the strike price are key factors to support investment in electricity storage technologies in the capacity auctions, which however must result in a trade-off with storage derating factors to ensure the security of supply.

The work of Fraunholz et al. (2021), which represents a rich and valid study, differs from the approach of this thesis in different aspects. Firstly, as for the other cited studies, it considers only electrical storage and sets aside long-term hydrogen storage, ignoring the sector-coupling dynamics that this would trigger. Secondly, it is focused on the influence of storage technologies derating and its relation with reliability requirements for participating in CRMs, representing, therefore, the impact of bearing risk with different combinations of these parameters instead of explicitly modelling risk aversion by using a risk metric.

In summary, literature about the hydrogen sector and its coupling with the power system is focused on the potential economic effects of a hydrogen market upscaling in relation to the operational benefits that electrolysis and long-term storage can provide, mainly in terms of flexibility and security of supply. However, when the discussion moves toward market design, the requirements and the possible biases that a hydrogen market entails are not considered. The debate on energy markets is more oriented on the impact of renewable energy on the electricity market design and how electrical short-term storage can be included in capacity mechanisms, with particular attention to derating factors. Furthermore, also risk effects are considered mainly from an electricity market perspective, just as the performances of support mechanisms such as CRMs or long-term agreements in correcting the "missing money problem".

The project proposes to link the three fields of literature previously discussed, namely the effects of hydrogen sector coupling, storage participation in CRMs and risk aversion on investment in generation capacity, in order to analyze the suitability and requirements of the hydrogen market to provide an effective backup for a coupled electricity and hydrogen system and enhance the integrated system adequacy. Indeed, even including capacity expansion problems, literature about the potential integration of a hydrogen market lacks considering the market design requirements that may be needed to ensure socially optimal investments in the presence of risk-averse investors. Similarly to experiences in electricity markets, imperfect conditions and in particular risk aversion could lead to underinvestment in hydrogen generation and storage capacity, which could require tailored market corrections able to hedge risk.

3
Approach and Conceptualization

The conceptualization of the problem is fundamental to clearly define the features of the system modelled and the focus of the analysis. This chapter proposes to outline the essential characteristics of the chosen approach, encompassing the method applied to model the problem and shaping the system itself, its actors and their interactions. Section 3.1 introduces the selected research method, outlining its specifics and arguing its suitability and limitations. Section 3.2 presents the conceptualization of the model, defining the system considered and the dynamics within it.

3.1. Research Method

This thesis aims to formulate a long-term equilibrium to investigate the effect of risk on investment and what market designs could hedge it in an integrated and decarbonized hydrogen and electricity system, where hydrogen long-term storage will provide the backup for the power sector. The core emphasis of the thesis lies in evaluating how investment allocations deviate from the socially optimal levels under varying degrees of risk aversion and diverse market designs, and how this impacts the integrated system adequacy. Given this central focus, it is fundamental that the selected methodology can effectively capture the interactions of different actors across sectors and include risk in the formulation. To address these requirements, the problem will be solved by formulating a stylized equilibrium model. This allows the individual modelling of each agent strategy and the representation of market dynamics within the hydrogen-electricity markets in the context of a non-competitive game (Höschle, 2018; Dagoumas & Koltsaklis, 2019). Furthermore, equilibrium models allow the consideration of uncertainty and risk, which are at the core of the study.

A long-term equilibrium is defined as an equilibrium that is hypothetically reached after a certain time if the boundary conditions remain the same. This choice has been made to reduce the computational burden; however, this does not reduce the validity of the results, as the insights gained will come from the trend analysis rather than from the absolute numbers.

The temporal scope is therefore limited to one year, with an hourly resolution. As implied from the definition of long-term equilibrium, the assumption is that this year repeats indefinitely. However, this one-year timeframe encapsulates the uncertainties introduced by the discrete scenarios of the stochastic model, which effectively represents 18 different years. The geographical perspective is of a single country resembling a potential Dutch scale, modelled as one node. The model does not allow for energy imports or exports. The energy system is built with a greenfield approach, without considering any pre-existing assets or constraints. At a technological level, all time periods are decoupled and no intertemporal constraints are applied, neglecting, e.g., ramping limits. An exception is made for storage, of which availability and arbitrage are key features and require coherent modelling. Investments are commissioned in reference technologies and not at a power plant level.

These general assumptions will be followed by specific assumptions in Chapter 5. However, it is important to remember that models are very sensitive to assumptions and an understanding of these is crucial for the quantitative analysis and the consequent policy recommendations (Pfenninger et al., 2014).

Uncertainty is one of the main features of the energy sector, inherently subject to weather-dependent generation of an increasingly vRES-based power system, future costs of different fuels or technologies, and the level of energy demand (Scott et al., 2021). These characteristics play an important role in driving investment in new generation capacity and trigger risk aversion in market players. It is therefore fundamental to consider uncertainty in the formulation of the model, which is done by introducing stochasticity to capture the probabilistic nature of uncertainties. The high computational cost associated with combining multiple uncertain inputs is outdone by the increased validity of the results (Scott et al., 2021). In this thesis, stochasticity will be introduced by formulating a set of discrete scenarios, which allow to consider the imperfect knowledge of the future in the decision-making process and reflect in the investment decisions. The main sources of uncertainty are the weather conditions, which affect the availability of vRES, and the electricity and hydrogen demand.

The stochastic long-term equilibrium model will be formulated to investigate the actors' strategies under the effect of uncertainty and risk aversion, and how these influence investments in the hydrogen sector. The resulting long-term equilibrium will provide information about the natural development led by a particular market design and, by comparing investments under different degrees of risk aversion, the effect of the latter on distorting the market outcome can be effectively analyzed. By explicitly modelling singular agents, the model will provide the opportunity to conduct further analysis out of the deviation from the socially optimal capacity mix and identify interdependences of the technologies. Analysis of the integrated system adequacy can be supported by an investigation of how availability is ensured and by who in a system driven by sector coupling, and what are possible costs and transfer of social welfare to ensure reliability.

3.2. Model Conceptualization

The integrated energy system model comprises the electricity and hydrogen sectors, represented by the supply and demand agents who interact in them. These agents can participate in an electricity EOM, a hydrogen EOM, an electricity capacity market and a hydrogen capacity market. The system is assumed decarbonized and therefore it does not consider a carbon market.

The renewable-based electricity backbone comprehends vRES generators based on wind and solar energy, biomass power plants equipped with carbon capture and storage, and hydrogen-fired turbines. Direct electrification is, in general, preferable to the use of hydrogen due to the low conversion efficiencies of electrolyzers and thermal generators (Bruninx et al., 2022). At the same time, the intermittency of wind and sun entails periods with insufficient available capacity, and consequently the need for dispatchable units. Considering the near-zero marginal costs of vRES technologies and the high investment costs of biomass power plants, hydrogen-fired turbines could represent a competitive solution for providing electricity in the decarbonized energy system during periods of vRES shortage. Hydrogen-fired turbines rely on the hydrogen market for the fuel supply, representing a sector-coupling technology between the electricity and hydrogen sectors.

To guarantee hydrogen availability and ensure the security of supply, adequate volumes of hydrogen must be produced and stored. Hydrogen production occurs through electrolyzers, powered by the renewable-based electricity backbone. They represent the other sector-coupling technology of the integrated system, acting in the opposite direction with respect to hydrogen-fired turbines. The hydrogen produced can directly fulfil the hard-to-abate sectors' demand or can be stored in salt caverns and reconverted into electricity by hydrogen turbines, providing long-term seasonal storage (Michalski et al., 2017).

For the sake of simplicity, short-term electricity storage is not considered. This would benefit the flexibility of the system but would not fundamentally affect the dynamics of long-term storage, which is the focus of this project.

It is important to highlight how sector-coupling agents and the electricity-hydrogen subsystems' interdependences that they trigger are critical issues of the integrated system. Indeed, hydrogen availability is a prerequisite for a reliable electricity sector. However, hydrogen availability is in turn dependent on electrolyzers and therefore, on the electricity dispatch itself. In this picture, hydrogen long-term storage in salt caverns can mitigate volatility by decoupling generation and consumption; however, this does not come without issues in terms of managing the storage supply in an unpredictable context. In particular, an appropriate valuing of storage and the related assets' capacity could be fundamental considering possible inefficiencies of scarcity pricing, as discussed in Chapter 1.

The long-term equilibrium between investment and operational decisions in the electricity market and in the hydrogen market is formulated as an equilibrium problem, in which each agent pursues its own strategy by optimizing its objective function. In the context of the non-cooperative game, the market-clearing constraints are the linkage between the strategies of the agents. They ensure the market balance and provide the prices on which agents base their investment decisions. As they are assumed price-taking, agents cannot behave strategically and do not have market power, but only rely on hydrogen and electricity prices. Also, market participants do not share information about their decision variables.

In general, the system is represented by a set of agents, each one formulated by its profit function. It is assumed that each generator company can invest in only one type of technology, as diversifying the investment portfolio would represent the possibility of internally hedging risk (Kaminski, 2022).

Figure 3.1 presents the full model and the interactions within the markets, where the arrows coming from the market represent the prices that the agents receive, while the arrows going to the markets represent the quantities the agents offer or demand. The functioning of the markets is presented in the following sections.

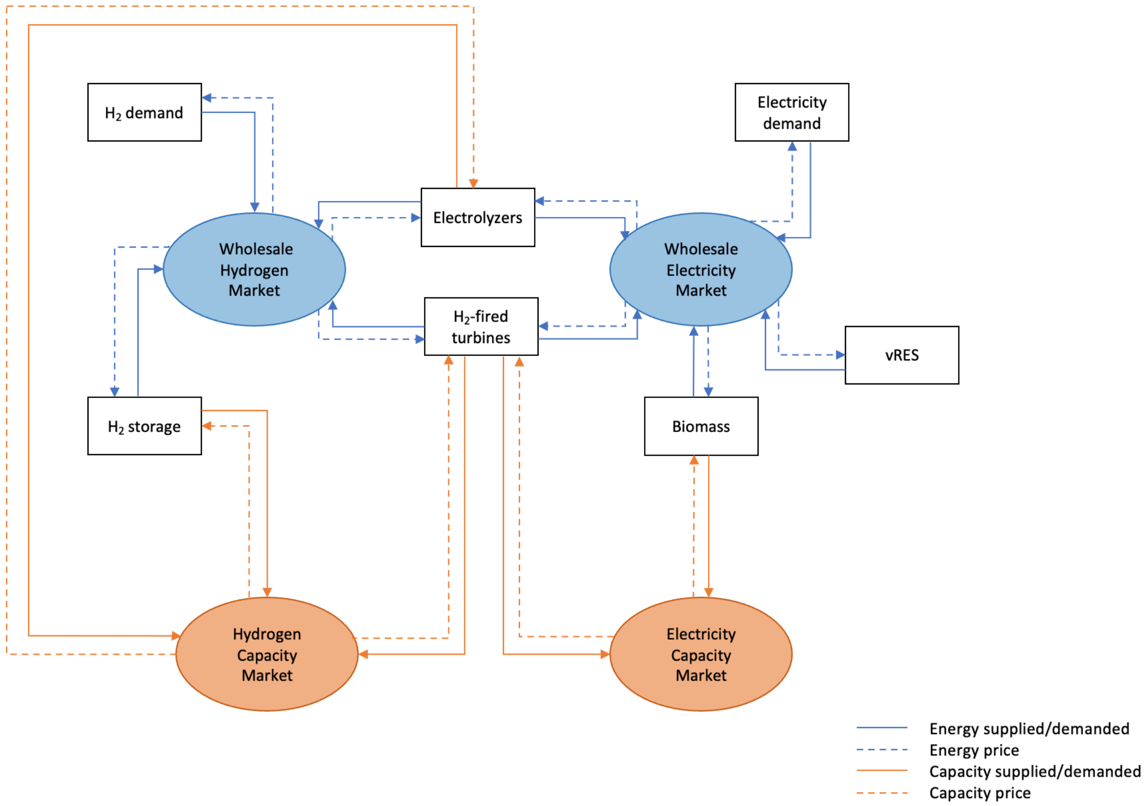


Figure 3.1: Representation of the integrated electricity and hydrogen markets and their participants

3.2.1. Energy-Only Markets

The integrated energy market consists primarily of a wholesale electricity market and a wholesale hydrogen market, both cleared hourly. Within the respective market, generator companies offer the amount of energy that they are willing to generate to the hourly energy market, and consumers adjust their energy demand based on the market price. Notably, sector-coupling agents and storage function as demand agents, leading to the emergence of endogenous demand variables as outcomes of market clearings. Again, importing and exporting energy is not allowed.

Each agent of the supply side represents a distinct technology and decides on the capacity to invest in and the volume of energy to offer, be it in the form of electricity or hydrogen. Generators recover their investment costs and operational costs through market revenues, offering their energy in the wholesale market.

Electricity generators supply the wholesale electricity market based on their availability, differentiating dispatchable generators which are always available, i.e. hydrogen turbines and biomass generators, and non-dispatchable generators, which generation depends on weather conditions, i.e. wind and sun.

In the hydrogen market, electrolyzers represent the primary ”hydrogen generators”. Storage operators, on the other hand, ultimately take advantage of arbitrage between periods of low and high hydrogen prices to determine when to buy or sell hydrogen, thereby maximizing their utility (Gonzato et al., 2021). Therefore, storage in turn acts as both a demand and supply agent, adapting its role based on the market conditions (i.e. supply and demand balance and therefore market price). However, also storage discharge capacity and volume are modelled as market-driven, and investments in hydrogen storage are a result of the agent strategy.

On the demand side of each sector, consumers are represented aggregately by an inverse demand function. Consumers optimize their utility by adapting the amount of energy bought from the market as a function of the energy price. Demand agents are considered price-elastic up to a price cap, and served demand is therefore endogenously determined in the model. The flexibility provided by demand elasticity can help to reduce investment risk in new generation capacity by spreading scarcity rents across more hours, but it also influences the optimal level of peak-load capacity in the generation mix, thus impacting the capacity target of a capacity market (Kaminski et al., 2021). While short-term demand elasticity is likely to increase and, as a flexible resource, to improve the reliability of the system, it may introduce high social costs manifested through prolonged periods of scarcity prices (De Vries & Sanchez Jimenez, 2022). As sources of flexibility will coexist and have an impact on system adequacy, it is important to include them in the model to objectively assess the impact of a capacity market for hydrogen.

External demand agents consider their surplus from the energy market as the difference between their willingness-to-pay (WTP) and the energy price. A representation of the energy demand function is shown in black in Figure 3.2. The intersection with the supply function (in blue) represents the market-clearing procedure and determines the price λ^e_{dt} and the volume of energy served $e_{co,dt}$.

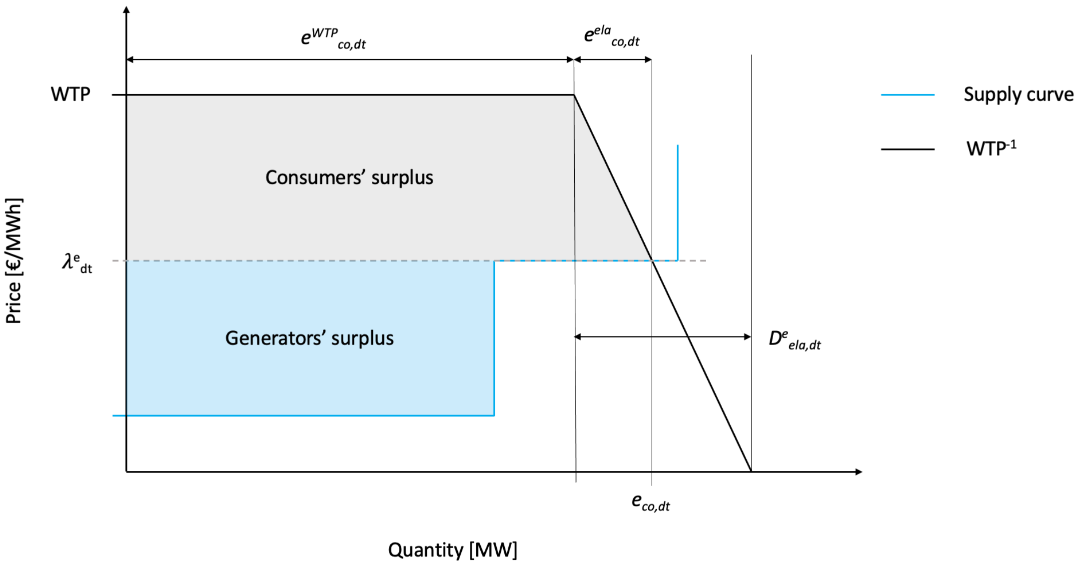


Figure 3.2: Inverse willingness-to-pay and supply functions

The price elastic demand function is made of two sections, the first one characterized by a constant WTP and the second one represented by a sloped curve. Both sections introduce price elasticity: the sloped section allows voluntary adjustment of the served demand as a function of the energy price, while the constant WTP section allows for involuntary curtailment whenever the price cap is reached.

The demand side of the electricity system consists of an aggregated demand agent and electrolyzers, which minimize the cost of procuring electricity to produce and sell green hydrogen.
The demand side of the hydrogen market is completed by an aggregated demand agent that represents the industrial and heating demand, and by the hydrogen turbines, which buy hydrogen as a fuel to provide backup electricity to the power system.

3.2.2. Capacity Markets

EOMs can be supported by forward capacity markets, which are here implemented for both the electricity sector and the hydrogen sector. They introduce a yearly remuneration for the firm capacity offered by generators.

The electricity capacity market allows the participation of only dispatchable generators. Even if the approach to derating vRES availability is still under debate (Kozlova & Overland, 2022), in this thesis vRES generators are excluded from it.

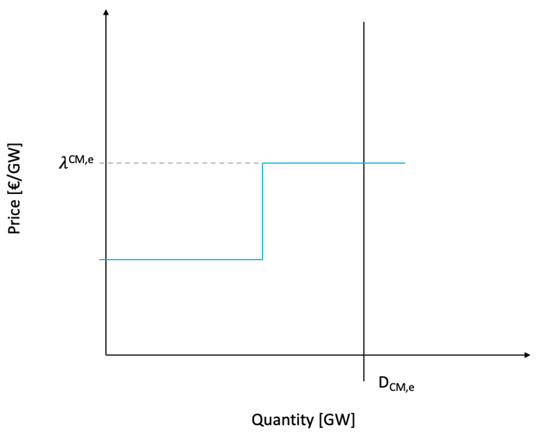
Within the hydrogen capacity market, hydrogen storage offers its discharge capacity alongside the electrolyzer capacity. These two actors are not in direct competition, as they fulfil different roles within the system. Electrolyzers represent the primary hydrogen supply, as they are the only process of hydrogen production in the model. They most likely run during periods of vRES abundance and store part of the hydrogen produced at advantageous prices. Their participation in the hydrogen capacity market is justified by the need for an adequate capacity able to fill up the storage to ensure its availability during peak electricity demand. Despite their dependence on vRES availability, they are not derated, as the model assumes that storage is responsible for guaranteeing availability during scarcity periods.

Hydrogen storage participates by offering only its discharge capacity, which is expected to contribute to covering the residual hydrogen load. In particular, it should back up the hydrogen turbine capacity by ensuring hydrogen availability. The hydrogen capacity market does not remunerate for storage volume or the availability of hydrogen. Discharge capacity, however, is not derated. Its long-term feature implies a storage volume that is expected to suffice for potential discharge duration needs for a significant portion of the year. However, this could be stressed in case of prolonged periods without wind and sun, and potential underinvestment would undermine the hydrogen backup.

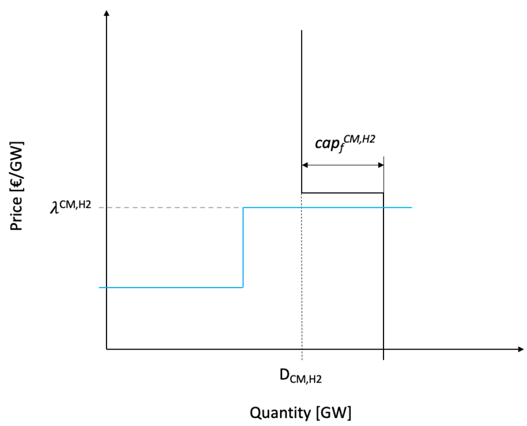
The exogenous capacity demand is considered inflexible in both the capacity markets, with the costs of capacity being transposed to the consumers.

For the electricity capacity market, as presented in Figure 3.3(a) this is the only demand term.

On the other hand, in the hydrogen market hydrogen-fired turbines represent a demand agent. As they are considered dispatchable generators within the power sector but depend on hydrogen availability, they have to ensure their availability to participate in the electricity capacity market. To do so, they explicitly express their demand for hydrogen capacity as presented in Figure 3.3(b). This allows them to ensure that the generation capacity they are offering in the electricity capacity market is covered by the hydrogen capacity that they are paying for. In this model, this is in general guaranteed by discharging storage. However, it must be noticed that storage does not ensure an adequate state of charge, and the model does not penalize hydrogen turbines or hydrogen storage for the potential unavailability of hydrogen. A similar reasoning could be applied to the demand for electricity by electrolyzers, which however do not run during periods of peak electricity demand and can be in principle substituted by storage discharge. It is therefore assumed that a firm capacity demand term for electrolyzers is not needed.



(a) Electricity capacity market demand and supply functions - The capacity demand is exogenous and inelastic



(b) Hydrogen capacity market demand and supply functions - The exogenous and inelastic capacity demand is completed by the firm capacity demand required by the hydrogen-fired turbine companies

Figure 3.3: Demand and supply functions of the (a) electricity and (b) hydrogen capacity markets

3.2.3. Risk Aversion

In order to evaluate the influence of uncertainty on investment decisions, a proper metric to model risk-averse investors is needed. Among the others, Conditional Value at Risk (CVAR) has gained popularity in scientific literature thanks to its mathematical properties and suitability for reflecting the true weight of the worst-case scenarios tail.

CVAR is in principle a coherent risk measure which can be formulated as continuous and convex, enabling a convenient application in mathematical optimization (Kaminski, 2022). Given a distribution of scenarios ordered by increasing profit, CVAR can be interpreted as the mean value of the worst-case tail, namely the set of scenarios with a cumulative probability of β. Therefore, CVAR takes into account both the magnitude and likelihood of potential losses. β is a parameter which describes the degree of risk aversion and can assume values from 0 to 1. The smaller is β, the shorter the worst-case tail, and therefore the higher the degree of risk aversion (Kaminski, 2022). When β is equal to one, the tail aligns with the entire probability distribution, thereby simplifying the case to the risk-neutral scenario, and the CVAR formulation becomes equivalent to the expected profit.

CVAR is based upon the concept of Value at Risk (VAR), another widely used risk metric. VAR is defined as the most positive outcome of the scenarios with a cumulative probability lower or equal to β:

$$VAR_{\beta}(S) = max\{\Pi s | F_s(\Pi_s) \leq \beta\} \tag{3.1}$$

where F_S is the cumulative probability of the profit of a scenario Π_s. However, VAR is in general less informative than CVAR, as it does not consider the shape of the tail of the worst scenarios, which is indeed defined as the set of scenarios with profit lower or equal to the VAR.

Given a set of decision variables χ, a set of scenarios S and the associated probabilities P_s and profits Π_s, the formulation of the CVAR problem is (Rockafellar & Uryasev, 2000):

$$\max_{\chi} \quad CVAR = \frac{1}{\beta} \sum_{s \in S^*} P_s \Pi_s(\chi) \tag{3.2}$$

$$\text{where} \qquad S^* = \{s \in S | \Pi_s \leq VAR_{\beta}(S)\} \tag{3.3}$$

Rockafellar & Uryasev (2000) also proposes a linear reformulation of CVAR, which simplifies the complexity of the implementation of the original formulation. The linear reformulation introduces two auxiliary variables, α and u_s. It is proven that α coincides with the VAR, while u_s represents the profit difference to the VAR of the scenarios of the worst-case tail (Kaminski, 2022). Indeed, when the profit of a scenario Π_s is greater than the VAR, Constraint (3.5) is not binding and u_s is zero, therefore it does not affect the objective. On the other hand, when the profit of a scenario Π_s is less than the VAR, Constraint (3.5) becomes binding and u_s affects the objective function.

$$\max_{\chi, \alpha, u} \quad CVAR = \alpha - \frac{1}{\beta} \sum_{s} P_s u_s \tag{3.4}$$

$$\text{subject to} \qquad \alpha - \Pi_s \leq u_s \qquad (\delta_s) \qquad \forall s \tag{3.5}$$

$$0 \leq u_s \tag{3.6}$$

$$\alpha \in \mathbb{R} \tag{3.7}$$

4
Model Definition and Formalization

The formulation of the problem and its translation in a suitable programming language represents the core of the methodology, allowing to create the model which represents the conceptualized system. This chapter leads the transition from the conceptual problem to the implemented one, explaining what are the expedients used to properly represent the system. Section 4.1 explains the basic features of the model, while Section 4.2 presents the mathematical formulation of the singular agents' problems and the linking constraints. This is followed by Section 4.3, which explains the algorithm used to solve the problem. The chapter is closed by Section 4.4, which validates the model by testing the formulation and the solution algorithm performance.

4.1. Implementation

To compute the long-term equilibrium, the model simulates the evolution of the integrated energy markets by considering one year, assuming the boundary conditions would not change and therefore this year would repeat itself indefinitely. Uncertainty is introduced in the model by using discrete scenarios, which differ in the electric load, availability factors dependent on weather conditions, and hydrogen demand.

To reduce the computational burden, the model uses 8 representative days for each scenario by using a time series aggregation method. Time series aggregation methods are commonly used to represent intra-annual temporal variability in an aggregated form (Gonzato et al., 2021). These methods select representative periods within a time series and assign them a weight based on their ability to adequately represent demand and vRES generation patterns, and therefore economic and operational impact. By reducing redundancy in a dataset with these methods, computational time can be significantly reduced while obtaining a good approximation of the solution. Considering that each day is divided into hourly timesteps, the full year in terms of demand and availability factors of vRES is approximated by using a total of 192 timesteps for each scenario.

4.2. Mathematical Formulation

As introduced, in equilibrium problems each agent is represented in the model by the optimization problem of its utility function. The strategies here formulated refer to the stochastic equilibrium problem with risk-averse agents and with a capacity market for dispatchable electricity generators and a capacity market for hydrogen generators in place. The utility function of each agent is composed of a weighted sum of the expected profit and the Conditional Value at Risk. The latter is formulated as presented in subsection 3.2.3 and represents an additional risk premium that the decision-maker is willing to pay for mitigating the potential downside risk associated with the profit. The two terms are weighted by γ, which can take values from 0 to 1.

During the analysis of the results, the following formulations will be deconstructed to investigate the risk-neutral case, different degrees of risk aversion and the implications of the absence and presence of capacity markets.

4.2.1. RES-based Generation Companies

Variable renewable energy generation companies r try to maximize the weighted sum of the expected profit $\sum_y P_y \Pi_{r,y}$ and the $CVAR_r$ by selling electricity while paying investment and operational costs. For each scenario y, the profit $\Pi_{r,y}$ is calculated in Equation (4.8) as the sum of the difference between the electricity price from the EOM $\lambda^e_{dt,y}$ and the operational costs VC_r multiplied by the electricity sold $e_{r,dt,y}$ at each time step t every selected representative day d weighted by the $W_{d,y}$. The investment costs, obtained by multiplying the installed capacity cap_r by the capital costs IC_r, are subsequently deducted from this amount. Additionally, renewable generators can offer capacity $cap_{r,CM}$ in the electricity capacity market. This is accounted for by the product of the capacity they offer $cap_{r,CM}$ and the capacity price λ^e_{CM}, corrected for their dispatchability by the derating factor Φ.

Each renewable energy generation company r, therefore, decides to invest in a certain amount of capacity cap_r, offer to the capacity market a certain amount $cap_{r,CM}$ of that, and sell in the hourly EOM a certain amount of electricity $e_{r,dt,y}$ by solving the following optimization problem[1]:

$$\max_{\chi_r \in X_r} \quad \gamma \sum_y P_y \Pi_{r,y} + (1-\gamma) CVAR_r \tag{4.1}$$

subject to

$$0 \le e_{r,dt,y} \le cap_r A_{r,dt,y} \qquad (\underline{\delta}^e_{r,dt,y}, \overline{\delta}^e_{r,dt,y}) \qquad \forall d,t,y \tag{4.2}$$

$$0 \le cap_r \qquad (\overline{\delta}^c_r) \tag{4.3}$$

$$0 \le cap_r^{CM,e} \le \Phi cap_r \qquad (\underline{\delta}^{CM}_r, \overline{\delta}^{CM}_r) \tag{4.4}$$

$$\alpha_r - \Pi_{r,y} \le u_{r,y} \qquad (\delta^{CVAR}_{r,y}) \qquad \forall y \tag{4.5}$$

$$0 \le u_{r,y} \qquad \forall y \tag{4.6}$$

$$\alpha_r \in \mathbb{R} \tag{4.7}$$

with

$$\begin{aligned} \Pi_{r,y}(\chi_{r,y}, \lambda^e_{dt,y}, \lambda^e_{CM}) = & \sum_d W_{d,y} \sum_t (\lambda^e_{dt,y} - VC_r) e_{r,dt,y} \\ & - cap_r IC_r \\ & + \Phi \lambda^e_{CM} cap_r^{CM,e} \end{aligned} \tag{4.8}$$

$$CVAR_r = \alpha_r - \frac{1}{\beta} \sum_y P_y u_{r,y} \tag{4.9}$$

where Constraint (4.2) limits the power the electricity offered to the capacity installed cap_r corrected by the availability factor of that time step $A_{r,dt,y}$. Furthermore, Constraint (4.4) limits the capacity offered to the capacity market $cap_r^{CM,e}$ to the installed capacity cap_r, again corrected by the derating factor Φ.

[1] For the sake of implementation of the solution algorithm, the optimization problem is implemented in the model as the minimization problem of the opposite of the weighted sum of the expected profit and CVAR

4.2.2. Hydrogen-fired Turbine Companies

Similarly to RES power generation companies, hydrogen-fired turbine companies maximize their expected profit $\sum_y P_y \Pi_{f,y}$ and the $CVAR_f$ based on installed capacity, the electricity sold and the hydrogen bought in the wholesale markets. Additionally, they decide on how much of their capacity they offer in the electricity CM and how much of firm capacity they are willing to pay for in the hydrogen CM. For each scenario y, the profit $\Pi_{f,y}$ is expressed in Equation (4.19). The first row represents the profit dependent on generation, calculated as the sum of the difference between the electricity price from the EOM $\lambda^e_{dt,y}$ and the operational costs VC_f multiplied by the electricity sold $e_{f,dt,y}$ at each time step t every selected representative day d weighted by the $W_{d,y}$. Additionally, they have a variable cost dependent on the cost of the fuel in the hydrogen market $\lambda^{H_2}_{dt,y}$ multiplied by the amount of hydrogen bought $h_{f,dt,y}$. The investment costs obtained by multiplying the installed capacity cap_f multiplied by the capital costs IC_f are then subtracted in the second row of Equation (4.19). The third row represents the costs and revenues from the capacity markets: when an electricity capacity market is present, they receive compensation for the capacity they provide to the capacity market, denoted as $cap_{f,CM}$, equal to the product of the latter and the capacity price of power generation λ^e_{CM}. On the other hand, the costs of the firm capacity explicitly requested to the hydrogen sector cap_f^{CM,H_2} by the hydrogen-fired turbine companies are determined by multiplying the latter by the capacity price of hydrogen generation λ^{CM,H_2} and they are subtracted in the profit function.

Each hydrogen-fired turbine company, therefore, decides to invest in a certain amount of capacity cap_f and offer a certain amount $cap_{f,CM}$ of it to the capacity market and to buy enough hydrogen in the hourly EOM hydrogen market $h_{f,dt,y}$ to sell in the hourly EOM a certain amount of electricity $e_{f,dt,y}$ by solving the following optimization problem:

$$\max_{\chi_s \in X_s} \quad \gamma \sum_y P_y \Pi_{f,y} + (1-\gamma) CVAR_f \tag{4.10}$$

subject to

$$
\begin{aligned}
0 \leq e_{f,dt,y} &\leq cap_f && (\underline{\delta}^e_{f,dt,y}, \overline{\delta}^e_{f,dt,y}) && \forall d,t,y && (4.11)\\
e_{f,dt,y} &= \eta_f h_{f,dt,y} && && \forall d,t,y && (4.12)\\
0 &\leq cap_f && (\overline{\delta}^c_f) && && (4.13)\\
0 \leq cap_f^{CM,e} &\leq cap_f && (\underline{\delta}_f^{CM,e}, \overline{\delta}_f^{CM,e}) && && (4.14)\\
\frac{cap_f}{\eta_f} &= cap_f^{CM,H_2} && (\delta_f^{CM,H_2}) && && (4.15)\\
\alpha_f - \Pi_{f,y} &\leq u_{f,y} && (\delta^{CVAR}_{f,y}) && \forall y && (4.16)\\
0 &\leq u_{f,y} && && \forall y && (4.17)\\
\alpha_f &\in \mathbb{R} && && && (4.18)
\end{aligned}
$$

with

$$
\begin{aligned}
\Pi_{f,y}(\chi_{f,y}, \lambda^e_{dt,y}, \lambda^{H_2}_{dt,y}, \lambda^{CM,e}, \lambda^{CM,H_2}) = & \sum_d W_{d,y} \sum_t \Big[(\lambda^e_{dt,y} - VC_f) e_{f,dt,y} - \lambda^{H_2}_{dt,y} h_{f,dt,y} \Big] \\
& - cap_f IC_f \\
& + \lambda^{CM,e} cap_f^{CM,e} - \lambda^{CM,H_2} cap_f^{CM,H_2} \qquad (4.19)
\end{aligned}
$$

$$CVAR_f = \alpha_f - \frac{1}{\beta} \sum_y P_y u_{f,y} \tag{4.20}$$

Hydrogen-fired turbines are considered dispatchable generators as the hydrogen supply is ultimately dependent on the hydrogen market. Therefore, their capacity is not derated and their electricity production is constrained in Constraint (4.11) only for the nominal capacity cap_f. Equation (4.12) links the amount of electricity produced $e_{f,dt,y}$ to the amount of hydrogen used as fuel $h_{f,dt,y}$ via the turbine efficiency η_f. Hydrogen volumes are already expressed as energy.

In the context of capacity markets, the capacity they can offer to the electricity capacity market $cap_f^{CM,e}$ is limited by the total installed capacity cap_f by Constraint (4.14). Similarly, the demand for hydrogen supply firm capacity $cap_f^{CM,H2}$ is required to be equal to the capacity offered in the electricity capacity market corrected by the efficiency in Constraint (4.15), in order to express the real demand for hydrogen which can ensure the reliability of hydrogen turbines in the electricity sector.

4.2.3. Electrolyzer Companies

Electrolyzers are the technology in which hydrogen generation companies invest, trying to maximize the weighted combination of the expected profit $\sum_y P_y \Pi_{f,y}$ and the $CVAR_f$. Each scenario's profit $\Pi_{ez,y}$ is calculated in Equation (4.29). Th first row calculates the profit dependent on the generation as the sum of the difference between the hydrogen price from the EOM $\lambda_{dt,y}^{H_2}$ and the operational costs VC_{ez} multiplied by the hydrogen sold $h_{ez,dt,y}$ at each time step t every selected representative day d weighted by the $W_{d,y}$. Furthermore, the electricity costs for providing electricity are subtracted, obtained by multiplying the electricity needed to power electrolyzers $e_{ez,dt,y}$ by the electricity price $\lambda_{dt,y}^{e}$. The second row of Equation (4.29) subtracts the investment costs, obtained by multiplying the installed capacity cap_{ez} by the capital costs IC_{ez}. Finally, the third row sums the revenues from the hydrogen capacity market, calculated as the product of the capacity price for hydrogen generation λ^{CM,H_2} and the electrolyzers capacity offered cap_{ez}^{CM,H_2}.

Summarizing, hydrogen generation companies decide to invest in a certain amount of electrolyzers capacity cap_{ez} and to buy enough electricity $e_{ez,dt,y}$ from the hourly electricity EOM to produce and sell hydrogen $h_{ez,dt,y}$ in the hourly hydrogen EOM by solving the following optimization problem:

$$\max_{\chi_{ez}\in X_{ez}} \quad \gamma \sum_y P_y \Pi_{ez,y} + (1-\gamma) CVAR_{ez} \tag{4.21}$$

$$\begin{aligned}
\text{subject to} \quad & 0 \le e_{ez,dt,y} \le cap_{ez} && (\underline{\delta}^{e}_{ez,dt,y}, \overline{\delta}^{e}_{ez,dt,y}) && \forall d,t,y && (4.22)\\
& h_{ez,dt,y} = \eta_{ez} e_{ez,dt,y} && && \forall d,t,y && (4.23)\\
& 0 \le cap_{ez} && (\overline{\delta}^{c}_{ez}) && && (4.24)\\
& 0 \le cap_{ez}^{CM,H_2} \le \eta_{ez} cap_{ez} && (\underline{\delta}^{CM,H_2}_{ez}, \overline{\delta}^{CM,H_2}_{ez}) && && (4.25)\\
& \alpha_{ez} - \Pi_{ez,y} \le u_{ez,y} && (\delta^{CVAR}_{ez,y}) && \forall y && (4.26)\\
& 0 \le u_{ez,y} && && \forall y && (4.27)\\
& \alpha_{ez} \in \mathbb{R} && && && (4.28)
\end{aligned}$$

$$\begin{aligned}
\text{with} \quad \Pi_{ez,y}(\chi_{ez,y}, \lambda^{e}_{dt,y}, \lambda^{H_2}_{dt,y}, \lambda^{CM,H_2}) = & \sum_d W_{d,y} \sum_t \Big[(\lambda^{H_2}_{dt,y} - VC_{ez}) h_{ez,dt,y} - \lambda^{e}_{dt,y} e_{ez,dt,y} \Big] \\
& - cap_{ez} IC_{ez} \\
& + \lambda^{CM,H_2} cap_{ez}^{CM,H_2} \qquad (4.29)\\
CVAR_{ez} = & \ \alpha_{ez} - \frac{1}{\beta} \sum_y P_y u_{ez,y} \qquad (4.30)
\end{aligned}$$

Constraint (4.23) links the amount of hydrogen produced $h_{ez,dt,y}$ to the electricity consumption $e_{ez,dt,y}$ by the electrolyzer's efficiency η_{ez}. Additionally, Constraint (4.22) limits hydrogen production by limiting the electricity input $e_{ez,dt}$ to the installed capacity cap_{ez}. Constraint (4.25) limits the capacity offered to the hydrogen capacity market cap_{ez}^{CM,H_2} to the installed capacity cap_{ez} corrected by the efficiency η_{ez}.

4.2.4. Hydrogen Storage Companies

Hydrogen storage companies maximize the weighted sum of expected profit $\sum_y P_y \Pi_{ez,y}$ and the $CVAR_s$ taking advantage of time arbitrage to buy and sell hydrogen in the hydrogen market whenever it is more convenient. The scenarios' profit $\Pi_{s,y}$ is formulated in Equation (4.43). The first row represents the costs dependent on hydrogen volumes, calculated as the sum of the difference between the hydrogen price $\lambda^{H_2}_{dt,y}$ from the EOM and the operational costs VC_s multiplied by the hydrogen extracted and sold $dh_{dt,y}$ during discharging periods at each time step t every selected representative day d weighted by the $W_{d,y}$. From this, the sum of the hydrogen price $\lambda^{H_2}_{dt,y}$ from the EOM and the operational costs VC_s multiplied by the hydrogen bought $ch_{dt,y}$ during charging periods at each time step t every selected representative day d weighted by the $W_{d,y}$ is subtracted. Investment costs are expressed by the sum of the product of the installed capacity P and its capital costs IC_P and the product of the volume of the storage V and its capital costs IC_V. They are then subtracted in the second row. Finally, the third row sums the revenues from the hydrogen capacity market, calculated as the product of the capacity price for hydrogen generation λ^{CM,H_2} and the storage discharge capacity offered cap^{CM,H_2}_s.

Storage operators companies decide to invest in a certain volume of storage V and a certain capacity P and to sell dh_{dt} and to buy ch_{dt} in the hourly hydrogen wholesale market by solving the following optimization problem:

$$\max_{\chi_s \in X_s} \quad \gamma \sum_y P_y \Pi_{s,y} + (1-\gamma) CVAR_s \tag{4.31}$$

subject to

$$\begin{aligned}
& 0 \le dh_{dt,y} \le P && (\underline{\delta}_{dh,dt,y}, \overline{\delta}_{dh,dt,y}) \quad \forall d,t,y && (4.32)\\
& 0 \le ch_{dt,y} \le P && (\underline{\delta}_{ch,dt,y}, \overline{\delta}_{ch,dt,y}) \quad \forall d,t,y && (4.33)\\
& 0 \le P && (\overline{\delta}_P) && (4.34)\\
& 0 \le V && (\overline{\delta}_V) && (4.35)\\
& 0 \le cap^{CM,H_2}_s \le P && (\underline{\delta}^{CM,H_2}_s, \overline{\delta}^{CM,H_2}_s) && (4.36)\\
& 0 \le SOC_{dt,y} \le V && (\underline{\delta}_{SOC,dt,y}, \overline{\delta}_{SOC,dt,y}) \quad \forall d,t,y && (4.37)\\
& 0 \le SOC^0_{d,y} \le V && (\underline{\delta}_{SOC^0_{d,y}}, \overline{\delta}_{SOC^0_{d,y}}) \quad \forall d,y && (4.38)\\
& SOC_{dt,y} = SOC_{dt-1,y} + \eta_{ch} ch_{dt,y} - dh_{dt,y}/\eta_{dh} && (\beta_{dt,y}) \quad \forall d,t,y && (4.39)\\
& \alpha_s - \Pi_{s,y} \le u_{s,y} && (\delta^{CVAR}_{s,y}) \quad \forall y && (4.40)\\
& 0 \le u_{s,y} && \forall y && (4.41)\\
& \alpha_s \in \mathbb{R} && && (4.42)
\end{aligned}$$

with

$$\begin{aligned}
\Pi_{s,y}(\chi_s, \lambda^{H_2}_{dt,y}, \lambda^{CM,H_2}) = & \sum_d W_{d,y} \Big[\sum_t (\lambda^{H_2}_{dt,y} - VC_s) dh_{dt,y} - \sum_t (\lambda^{H_2}_{dt} + VC_s) ch_{dt} \Big] \\
& - P \cdot IC_P - V \cdot IC_V \\
& + \lambda^{CM,H_2} cap^{CM,H_2}_s
\end{aligned} \tag{4.43}$$

$$CVAR_s = \alpha_s - \frac{1}{\beta} \sum_y P_y u_{s,y} \tag{4.44}$$

Constraint (4.32) and Constraint (4.33) limit the amount of hydrogen hourly exchanged to the capacity of the storage plant. On the other hand, Constraint (4.37) and Constraint (4.38) limit the amount of hydrogen stored at every moment to the volume of the storage facility. With regards to the capacity offered in the hydrogen capacity market, Constraint (4.36) limits it to the discharge capacity P.

Constraint (4.39) is an auxiliary constraint that updates the state of charge each timestep summing the hydrogen charged or subtracting the hydrogen discharged in the previous timestep considering the respective process efficiency η_{ch} and η_{dh} and considering the electricity consumption of the compressors and expanders.

As previously introduced, the model works with representative periods to reduce the computational cost. Selecting representative periods can complicate modelling inter-period arbitrage, which is a fundamental feature of long-term storage operation and represents its main source of revenue. As these periods are considered independent and a daily scale is not large enough to represent the seasonal storage dynamics, inter-period arbitrage cannot be taken into account (Kotzur et al., 2018). This means neglecting inter-period states and devaluing the contribution of mid and long-term energy storage technologies, which may lead to their exclusion from investors' interest (Gonzato et al., 2021). Additionally, ignoring the potentially important contribution of seasonal storage in terms of system efficiency and security of supply is even more critical with high shares of vRES.

To allow long-term storage participation in an investment setting, the Enhanced Representative Days (ERD) formulation proposed by Gonzato et al. (2021) is implemented. The ERD method defines the maximum energy changes (positive and negative) over representative days and extends them to non-representative days using a linear combination of representative days. This is possible due to the linearity of the storage agent problem and is not dependent on other problems that contribute to the equilibrium (Kotzur et al., 2018).

By representing the base state of charge for all days using a linear combination of energy changes over representative days and using previously derived maximum energy changes, it is possible to ensure the state of charge remains within storage limits. This approach extends the state of charge of long-term storage throughout the year and accounts for inter-period arbitrage, providing a more accurate representation of the value of long-term storage technologies. The functioning of the ERD is illustrated in Figure 4.1.

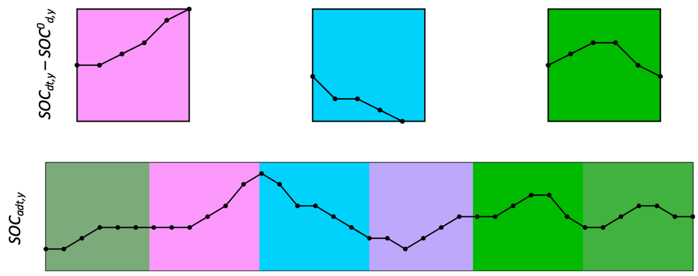


Figure 4.1: Storage state of charge representation using ERD for 6 periods, of which 3 are representative periods (Gonzato et al., 2021) - The top row shows the evolution of the state of charge $SOC_{dt,y}$ of 3 representative periods with respect to their initial state of charge $SOC^0_{d,y}$. The bottom row shows the evolution of the state of charge $SOC_{adt,y}$ over the whole year, which can be computed for non-representative periods as a linear combination of representative ones.

Firstly, an auxiliary variable Δ that represents the daily energy exchange of the storage of the day d for each scenario y is introduced:

$$\Delta h_{d,y} = \sum_{t \in T} (\eta_{ch} ch_{dt,y} - dh_{dt,y}/\eta_{dh}) \qquad (\gamma_{\Delta,y}) \qquad \forall d, y \tag{4.45}$$

It is now possible to define the base state of charge SOC^0 for all the days of the year.

$$SOC^0_{ad,y} = SOC^0_{ad-1,y} + \sum_{d \in D} V_{ad,d,y} \cdot \Delta h_{d,y} \qquad (\gamma_{SOC^0_{ad,y}}) \qquad \forall ad(2:end), y \tag{4.46}$$

where AD represents the set of all days of the year, both representative and non-representative, while $V_{ad,d,y}$ is the ordering matrix of scenario y that contains the coefficients of the linear combination of representative days to obtain the set of all days.

It is then possible to define the maximum positive and negative deviations from the base state of charge for representative periods:

$$0 \leq \Delta h^{max}_{d,y} \geq SOC_{dt,y} - SOC^0_{d,y} \qquad (\underline{\delta}_{max,dt,y}, \overline{\delta}_{max,dt,y}) \qquad \forall d,t,y \tag{4.47}$$
$$0 \leq \Delta h^{min}_{d,y} \geq SOC^0_{d,y} - SOC_{dt,y} \qquad (\underline{\delta}_{min,dt,y}, \overline{\delta}_{min,dt,y}) \qquad \forall d,t,y \tag{4.48}$$

And therefore to extend this definition to all the periods:

$$\Delta h^{max}_{ad,y} = \sum_{d \in D} V_{ad,d,y} \Delta h^{max}_{d,y} \qquad (\gamma_{max,ad,y}) \qquad \forall ad,y \tag{4.49}$$
$$\Delta h^{min}_{ad,y} = \sum_{d \in D} V_{ad,d,y} \Delta h^{min}_{d,y} \qquad (\gamma_{min,ad,y}) \qquad \forall ad,y \tag{4.50}$$

At this point, it is possible to impose the state of charge limits for all days:

$$SOC^0_{ad,y} + \Delta h^{max}_{ad,y} \leq V \qquad (\delta_{max,ad,y,lim}) \qquad \forall ad,y \tag{4.51}$$
$$SOC^0_{ad,y} - \Delta h^{min}_{ad,y} \geq 0 \qquad (\delta_{min,ad,y,lim}) \qquad \forall ad,y \tag{4.52}$$

Finally, a cyclic constraint is added to ensure the final state of charge is greater than the initial one:

$$SOC^0_{ad_0,y} \leq SOC^0_{ad_{end},y} + \sum_{d \in D} V_{ad_{end},d,y} \cdot \Delta h_{d,y} \qquad (\delta_{cycle}) \tag{4.53}$$

4.2.5. Electricity Consumers

Electricity consumers are considered from an aggregated perspective. The served demand is decomposed into an inelastic part and an elastic part, namely represented by $e^{WTP}_{co,dt,y}$ and $e^{ela}_{co,dt,y}$. Similarly to generation agents, demand agents are formulated as risk-averse. Aggregated electricity consumers aim to maximize a weighted sum of their expected utility $\sum_y P_y \Pi_{co,e,y}$ and the $CVAR_{co,e}$. The utility of each scenario $\Pi_{co,e,y}$ is the difference between the integrated inverse WTP function and costs for procuring energy and ensuring capacity as expressed Equation (4.58), of which formulation is inspired by Kaminski et al. (2021). Revenues are represented by the integrated inverse WTP function, of which the geometrical interpretation is shown in Figure 3.2 and refers to the terms within the square brackets in Equation (4.58). Costs are given by the product of the electricity EOM clearing price $\lambda^e_{dt,y}$ and the served electricity $e_{co,dt,y}$. Additionally, the second line of Equation (4.58) expresses how consumers have to pay for the capacity contracted in the electricity capacity market $D_{CM,e}$, as a means of insurance for the security of supply, which is however exogenously determined.

The aggregated electricity demand agent decides therefore how much electricity $e_{co,dt,y}$ is consumed by solving the following optimization problem:

$$\max_{\chi_{co,e} \in X_{co,e}} \quad \gamma \sum_y P_y \Pi_{co,e,y} + (1-\gamma) CVAR_{co,e} \tag{4.54}$$

where $D^e_{ela,dt,y} = \frac{WTP}{m}$ is the maximum quantity of demand that is price elastic, where m is the slope of the elastic section of the inverse WTP function.

$$\text{subject to} \quad 0 \le e^{WTP}_{co,dt,y} \le \psi D^e_{dt,y} \quad (\underline{\mu}^{WTP}_{dt,y}, \overline{\mu}^{WTP}_{dt,y}) \quad \forall d,t,y \tag{4.55}$$

$$0 \le e^{ela}_{co,dt,y} \le D^e_{ela,dt,y} \quad (\underline{\mu}^{ela}_{dt,y}, \overline{\mu}^{ela}_{dt,y}) \quad \forall d,t,y \tag{4.56}$$

$$\text{with} \quad e_{co,dt,y} = e^{WTP}_{co,dt,y} + e^{ela}_{co,dt,y} \tag{4.57}$$

$$\Pi_{co,e,y}(\chi_{co,e,y}, \lambda^e_{dt,y}) = \sum_d W_{d,y} \sum_t \Big[(WTP^e e_{co,dt} - (e^{ela}_{co,dt})^2 \frac{WTP^e}{2D^e_{ela,dt}}) - \lambda^e_{dt} e_{co,dt}\Big]$$
$$- \lambda^{CM,e} D_{CM,e} \tag{4.58}$$

$$CVAR_{co,e} = \alpha_{co,e} - \frac{1}{\beta} \sum_y P_y u_{co,e,y} \tag{4.59}$$

The demand is modelled as price elastic and therefore curtailment is allowed. Constraint (4.55) limits the constant WTP section to a certain fraction ψ of the demand $D^e_{dt,y}$. Constraint (4.56) limits the price-elastic section (of which buildup is explained in Section 5.2), allowing also demand increase, which is possible only for electricity prices less or equal to zero.

4.2.6. Hydrogen Consumers

The hydrogen consumers are modelled aggregated as an external demand agent, price elastic up to the WTP. The optimization problem is, again, the maximization of the weighted sum of the expected utility $\sum_y P_y \Pi_{co,h,y}$ and the $CVAR_{co,h}$. The definition of the utility is the same as the electricity demand agent. However, the hydrogen price elasticity $D^{H_2}_{ela}$ is constant and not dependent on the demand.

As in the electricity sector, consumers have to pay for the capacity contracted in the hydrogen capacity market, as a means of insurance for the security of supply of hydrogen. This is expressed in the second row of Equation (4.64) as the product of the hydrogen capacity price λ^{CM,H_2} and the exogenous capacity demand D_{CM,H_2}.

Therefore, the aggregated hydrogen demand agent maximizes the expected surplus by deciding how much hydrogen buy in the hourly hydrogen market $h_{co,dt,y}$ by solving the following optimization problem:

$$\max_{\chi_{co,h} \in X_{co,h}} \quad \gamma \sum_y P_y \Pi_{co,h,y} + (1-\gamma) CVAR_{co,h} \tag{4.60}$$

$$\text{subject to} \quad 0 \le h^{WTP}_{co,dt,y} \le \psi D^{H_2}_{dt,y} \quad (\underline{\mu}^{WTP,H_2}_{dt,y}, \overline{\mu}^{WTP,H_2}_{dt,y}) \quad \forall d,t,y \tag{4.61}$$

$$0 \le h^{ela}_{co,dt,y} \le D^{H_2}_{ela} \quad (\underline{\mu}^{ela,H_2}_{dt,y}, \overline{\mu}^{ela,H_2}_{dt,y}) \quad \forall d,t,y \tag{4.62}$$

$$\text{where} \quad h_{co,dt,y} = h^{WTP}_{co,dt,y} + h^{ela}_{co,dt,y} \tag{4.63}$$

$$\Pi_{co,h,y}(\chi_{co,h,y}, \lambda^{H_2}_{dt,y}) = \sum_d W_{d,y} \sum_t \Big[(WTP^{H_2} h_{co,dt,y} - (h^{ela}_{co,dt,y})^2 \frac{WTP^{H_2}}{2D^{H_2}_{ela}}) - \lambda^{H_2}_{dt,y} h_{co,dt,y}\Big]$$
$$- \lambda^{CM,H_2} D_{CM,H_2} \tag{4.64}$$

$$CVAR_{co,h} = \alpha_{co,h} - \frac{1}{\beta} \sum_y P_y u_{co,h,y} \tag{4.65}$$

In the same way as electricity demand, hydrogen demand formulation allows for curtailment too. Constraint (4.61) limits the constant WTP section to a certain fraction ψ of the demand $D^{H_2}_{dt,y}$, while Constraint (4.62) limits the price-elastic section.

4.2.7. Market Clearing

The electricity and hydrogen markets are the playing field of the agents, which take their decisions based on the prices provided by the markets and cannot influence them, i.e., agents are price-taking. In the model, the markets link the generation companies and the demand side by providing the balancing constraints to which each agent of the respective sector contributes.

In particular, the wholesale electricity market constrains the supply and demand actors who participate in it to the following market balance:

$$\sum_r e_{r,dt,y} + e_{f,dt,y} - e_{co,dt,y} - e_{ez,dt,y} = 0 \qquad ({\lambda'_{dt,y}}^{e}) \qquad \forall d,t,y \tag{4.66}$$

Similarly, the wholesale hydrogen market constrains its participant to the following market balance:

$$h_{ez,dt,y} + dh_{dt,y} - ch_{dt,y} - h_{co,dt,y} - h_{f,dt,y} = 0 \qquad ({\lambda'_{dt,y}}^{H_2}) \qquad \forall d,t,y \tag{4.67}$$

The dual variable of the energy balances can be interpreted as the weighted respective market price ($\lambda_{dt,y} = \lambda'_{dt,y}/W_{d,y}$).

The electricity capacity market has to be balanced too. However, the demand for power generation capacity $D_{CM,e}$ is exogenous and inflexible. The balancing constraint for the electricity capacity market is the following:

$$cap^{CM,e}_r + cap^{CM,e}_f = D_{CM,e} \tag{4.68}$$

Finally, the hydrogen capacity market has a balancing constraint in which the exogenous demand for capacity is completed by the demand for available capacity by the hydrogen-fired turbine generation companies:

$$cap^{CM,H_2}_s + cap^{CM,H_2}_{ez} = cap^{CM,H_2}_f + D_{CM,H_2} \tag{4.69}$$

4.3. Solution Approach

Equilibrium problems in the energy sector are usually formulated in Mixed-Complementarity Problems (MCP), which involve primal decision variables, such as investment and dispatch decisions, and dual decision variables, such as market prices. To solve these problems, various techniques can be used, such as reformulating MCP with KKT conditions, iterative approaches, or converting MCP to an equivalent optimization problem and solving it using conventional solvers (Kaminski, 2022).

To compute the equilibrium of the non-cooperative game formulated in this thesis, the Alternative Direction Method of Multipliers (ADMM) proposed by Höschle (2018) will be used. Previous works that applied this method to the energy sector are Höschle et al. (2018), Kaminski et al. (2021), and Mays et al. (2019), which have been inspiring in applying this method to deal with risk aversion.

ADMM is an iterative method that combines the dual decomposition and the augmented Lagrangian methods (Kaminski, 2022). This algorithm can be applied to optimization problems that are separable in local optimization subproblems linked by shared equality constraints. This is the case of a non-cooperative game in which each agent has its own separable strategy, and they are only coupled by the market clearing condition. It is important to mention that, if the convergence is in general guaranteed under certain assumptions, the uniqueness of the equilibrium is not. For details on the performance and convergence of the ADMM algorithm, the reader is referred to Höschle et al. (2018).

For the considered generation expansion planning, the non-cooperative game is formulated as an optimal exchange problem where agents' problems are aggregated and solved as optimization subproblems linked by market balance constraints. Equality constraints combine separable decision variables with their dual variables on the market clearing conditions (Höschle et al., 2018). This setup facilitates the iterative search for the prices that equate supply and demand and ensures that the strategies of the different agents coincide with the long-run equilibrium strategies (Bruninx et al., 2020).

The ADMM algorithm formulation is based on the augmented Lagrangian of the agents. The agents' strategies are updated iteratively by solving the minimization problem of the augmented Lagrangian and updating the market prices. The update steps based on the augmented Lagrangian are obtained from the KKT conditions of the equilibrium problem. In particular, the optimality conditions of minimizing the unaugmented Lagrangian must coincide with the KKT conditions of the correspondent equilibrium problem. For example, for a vRES generator, the augmented Lagrangian objective function is formulated as:

$$\begin{aligned}\min_{\chi_r^{k+1} \in X_r^{k+1}} \quad & \sum_y P_y \sum_d W_{d,y} \sum_t VC_r e^{k+1}_{r,dt,y} + cap_r^{k+1} IC_r \\ & \underbrace{- \sum_y P_y \sum_d W_{d,y} \sum_t \lambda^{e,k+1}_{dt,y} e^{k+1}_{r,dt,y}}_{\text{1st penalty term}} \\ & \underbrace{+ \frac{\rho^{EOM}}{2} \sum_y \sum_d W_{d,y} \sum_t (e^{k+1}_{r,dt,y} - e^k_{r,dt,y} + \overline{e}^k_{r,dt,y})^2}_{\text{2nd penalty term}} \end{aligned} \tag{4.70}$$

where $\overline{e}^k_{r,dt,y}$ is the imbalance of supply and demand for the k iteration divided by the number of participant agents N increased by 1. In general, for an electricity EOM participant, it is expressed as:

$$\overline{e}^k_{dt,y} = \frac{\sum_r e^k_{r,dt,y} + e^k_{f,dt,y} - e^k_{co,dt,y} - e^k_{ez,dt,y}}{N+1} \tag{4.71}$$

The augmented Lagrangian used as the objective function comprehends two penalty terms. The first penalty term is associated with the sharing constraint and the correspondent dual variable, while the second penalty term penalizes the change in the decision and the imbalance of the sharing constraint weighted by a penalty factor. As they refer to the market clearing conditions decision variables, the model presents a penalty term for the traded electricity, a penalty term for the traded hydrogen, and a penalty term related to the capacity offered for each capacity market. Each agent's objective function includes the penalty terms related to the specific market clearing conditions they contribute to.

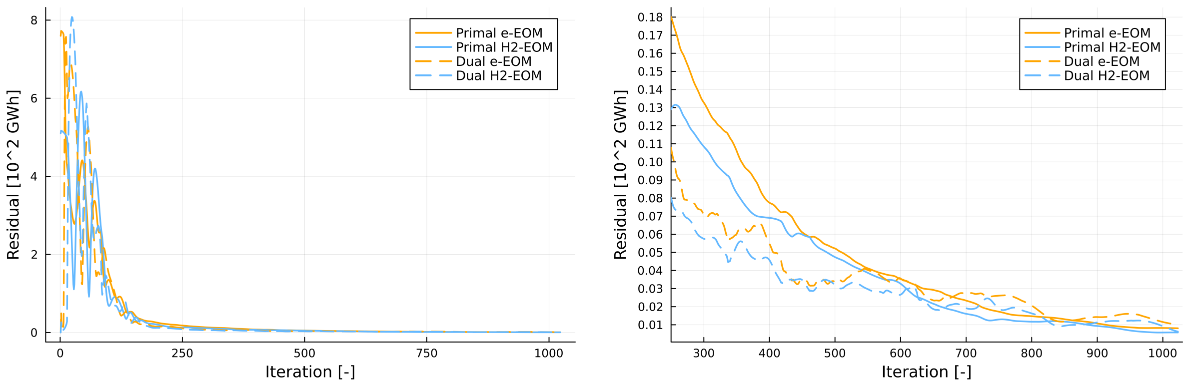
As introduced, the ADMM-based algorithm tries to find the equilibrium with a price adjustment procedure. In each iteration, the agents receive the prices and optimize their investment decision based on these. The decisions define the imbalances between demand and supply of the current iteration, which in turn affects the update of the market prices.
The price update step is computed as:

$$\lambda_{dt,y}^{k+1} = \lambda_{dt,y}^{k} - \rho \bar{e}_{dt,y}^{k} \tag{4.72}$$

The strategy and price update processes stop when the equilibrium is found or when the limit of 10000 iterations is reached. The equilibrium is computed by considering two stopping criteria, of which one represents the imbalances of the market clearings, while the other one the changes in the decision variables. The two stopping criteria are satisfied when simultaneously under a predefined threshold, which is in general weighted by ρ (convergence), the scale of the system demand, and the number of time steps. The primal stopping criteria is defined as the normalized by L2-norm sum of the primal residuals, which are the imbalances of each market clearing condition for each scenario and timestep. The dual stopping criteria is defined as the normalized by L2-norm sum of dual residuals, which are the differences of decision variables corrected by the average value of the decision variables of all agents between two consecutive iterations.

When the algorithm converges and a Nash equilibrium is obtained, i.e. when both stopping criteria are below the predefined threshold, the imbalances of the market clearing conditions converge to zero ($\bar{e}_{dt,y}^{k} = 0$) and the agents do not have incentives to change their decision anymore ($e_{r,dt,y}^{k+1} - e_{r,dt,y}^{k} = 0$). Therefore, at convergence, the second penalty term is eliminated, confirming how the augmented objective function presented in Equation (4.70) coincides with the objective function of the equilibrium problem presented in Appendix A.1.

Consequently, it can be affirmed that the solutions of the ADMM algorithm and the equilibrium problem formulation are identical considering the convergence criteria. Figure 4.2 presents the trend of residuals for a specific simulation of EOM with risk-averse agents ($\beta = 0.4$), and serves as proof of the validity of the solution method as long as it converges.



(a) Full simulation **(b)** Focus on the last 750 iterations

Figure 4.2: Convergence trend of residuals for the simulation of the EOM design case with risk-averse agents ($\beta = 0.4$)

The implementation of the equilibrium problem and the application of the ADMM algorithm is performed using the programming language Julia and the JuMP library. Agents' sub-optimization problems are solved iteratively with the Gurobi optimizer. The model has been built and expanded on a backbone of the code provided by Dr. Ir. Kenneth Bruninx, which included the set-up of the ADMM algorithm for a simplified version of the deterministic risk-neutral model with the EOM for renewable generators and electrolyzers. This has been extended to a stochastic model and reformulated to include risk aversion. Furthermore, it has been integrated with the remaining technologies presented and developed to include endogenous demand by formulating price-elastic demand agents. The market set-up has been integrated with the capacity markets.

4.4. Model Validation

In order to ensure the accuracy of the algorithm and the correct definition of the equilibrium problem, the model has to be validated. The validation is performed by formulating and solving the corresponding optimization problem and comparing the results with the equilibrium model solutions obtained with ADMM. The validation is conducted at an early stage for the deterministic formulation of the model. It is done before the introduction of risk aversion, as the latter precludes the possibility of formulating the equivalent optimization problem. On the other hand, the system can be considered complete in terms of agents' specifications but before implementing the capacity market.

The first step of the validation involves comparing the KKT (Karush-Kuhn-Tucker) conditions of the two formulations. By ensuring that the KKT conditions of the equilibrium problem coincide with those of the equivalent optimization problem, it can be proven that the two problems are equivalent.

The derivation of the unaugmented Lagrangian and the KKT conditions of the two problems can be found in Appendix A and B and confirm their conformity. There, it is verified that the two formulations of MCP coincide, except for the coefficient of the market price. This is due to the inclusion in the equilibrium model derivation of a weight factor W_d of the representative days, while it is missing in the optimization model derivation. Indeed, in the equilibrium model, market prices are explicitly used in the utility functions of the different agents and they are computed iteratively by the algorithm, while in the optimization problem, they are implicitly calculated as the dual variables of the market balance constraints. This, together with the inversion of the sign, is simply due to the market balance equality constraints, where the sign and the weight factor W_d are not influential. The two formulations differ only for this factor, which does not affect the validity of the model as it is simply a matter of interpretation. The dual variables can be scaled again with the weight factor to have a coherent comparison across the two models.

It has to be noted that the formulation presented in Appendix does not include the second penalty terms as it is implicitly assumed that the ADMM algorithm leads to convergence. As discussed in the previous section, at convergence, the second penalty terms cancel out and the KKT conditions of the augmented Lagrangian coincide with the Mixed Complementarity Problem (MCP) formulation of the equilibrium problem, ensuring the same solution (Höschle, 2018).

Further validation of the equilibrium problem is conducted by analyzing the net profit of the different agents of the equilibrium problem. These correspond to the value of the objective function of the singular agents' optimization problems. It is verified that they are at least 4 orders of magnitude smaller than the total revenues of the corresponding agent. This is further proof of the correct interpretation of the prices and proves that the equilibrium problem represents a perfectly competitive market, where firms earn (close to) zero profits in the long run.

The equivalent optimization problem is formulated in Julia and solved with Gurobi, a mathematical optimization solver. The analysis is conducted by comparing the optimal solution of the equivalent optimization problem, which aims to maximize the total social welfare (Appendix B), with the results obtained by the deterministic equilibrium model solved with ADMM. The tolerances of the hydrogen and electricity stopping criteria used for this simulation are weighted on 1% of the maximum demand of the respective sector.

By forcing the ADMM primal variables solution in the objective function of the equivalent optimization problem, the total social welfare can be computed based on the results found by ADMM. The relative difference in the social welfare value between the two formulations is of the order of 10^{-2}%, which can be ascribed to the different solution methods and the relative numerical inaccuracies.

A further investigation of the primal variables is performed, expecting that the results of the equilibrium problem solved with ADMM and the equivalent optimization problem coincide in terms of primal variables. Comparing the installed capacities for the different technologies of the two formulations, relatively small but relevant differences are found. The average relative difference in installed capacity is 1.75%, with an absolute difference peak of 0.78 GW. The volumes of energy exchanged between different actors similarly present small differences, but as they are ultimately dependent on the installed capacity, they are less meaningful in terms of deviations across the two models. However, it is important to note how energy exchanges are coherent and very similar in terms of trends and proportion. This cannot be considered a validation step itself but intuitively suggests how the two models are coherently formulated.

The differences are not negligible, but can ultimately be attributed to the scale used and the selected tolerance combined with a potential flat region where the optimal solution is located. Tests have been conducted on the scale of the problem and the tolerance used, noticing that increasing the scale of the system by using different units and reducing the latter would allow a more accurate solution, which however would come at a high computational cost and, in some cases, would undermine convergence.

Recalling that the two theoretical formulations coincide and the resulting total social welfare is the same, the analysis allows affirming that both solutions are correct. This confirms that the ADMM implementation is correct and suitable for the analysis.

5 Case Study

The relevance of the outcome of the model lies in the shift of the equilibrium consequent to the introduction of risk aversion. It is however important to base the model parameters on realistic assumptions, able to properly describe the agents' characteristics and their dependencies in order to enlighten relevant trends useful in a practical perspective. Chapter 3 and Chapter 4 presented the long-term equilibrium problem of an integrated electricity and hydrogen market within a single-market zone, inspired by the Dutch energy system.

The chapter is structured as follows. Section 5.1 presents the main assumptions with respect to the technologies considered, both in terms of costs and technological parameters. Section 5.2 explains how the data for electricity and hydrogen demand are gathered and manipulated. Section 5.3 presents a description of the scenarios used to contextualize the introduction of uncertainties in the model. Lastly, Section 5.4 presents the three different market designs tested in relation to the formulation presented in Chapter 4.

5.1. Technology Parameters

Considering the long-term perspective and recognizing the role of hydrogen as a promising long-term storage solution to effectively address the unpredictability of vRES, the system under consideration is modelled as fully decarbonized. In order to offer a comprehensive overview of the system, this section presents a description of the technologies involved. This serves to elucidate the key assumptions and provide insight into its overall complexity. To ensure a realistic characterization, the parameters and cost data for these technologies are derived from the open model dataset of PyPSA-Eur (Hörsch et al., 2023), which offers a robust representation of the European energy system. When other sources are used to complete the data, they are cited explicitly. The cost assumptions used refer to 2025 data, therefore RES may be relatively expensive.

Technologies are typically characterized by their overnight investment cost and their operational cost. The capital cost IC of each asset is obtained from the corresponding overnight cost OC, annualized with the discount rate r over the asset's lifetime n. A nominal discount rate r of 10% is used in the calculation. The formula applied to all investment assets in the model is expressed as follows:

$$IC = \frac{r \cdot OC}{1 - \frac{1}{(1+r)^n}} \tag{5.1}$$

In this model, renewable generators considered refer to electricity generators based on vRES, specifically wind and solar power, and biomass generators.

Wind and solar generators are characterized by an availability that is dependent on weather conditions and therefore, as their generation output is uncertain, these generators are considered non-dispatchable units. The model accounts for this intermittent availability by introducing time sets of availability factors, which are calculated based on the historical hourly power generation divided by the installed capacity of the Netherlands, using data retrieved from the European Network of Transmission System Operators for Electricity (ENTSO-E). The non-dispatchability of vRES technologies sparks a significant debate regarding their derating in capacity markets, which is a topic of ongoing debate (Kozlova & Overland, 2022). While recognizing the importance of this debate, it is necessary to remind that the inclusion of vRES in capacity markets falls outside the scope of this thesis, and vRES are therefore excluded from the capacity market in this model, which is done by setting their derating factor Φ in Equation (4.8) to 0.

vRES technologies are characterized by relatively high capital costs, equal to 529 $M€/GW$ for solar PV at utility scale and 1118 $M€/GW$ for wind turbine generators. At the same time, they presents low, near-zero operational costs, equal to 2 €$/MWh$ for solar PV and 5 €$/MWh$ for wind.

Biomass power plants are also included in the model and, as inter-temporal constraints are neglected, they serve as flexible decarbonized generators. These power plants exhibit high overnight costs of 4400 $M€/GW$, along with significant operational costs. Biomass feedstock is assumed to be consistently available and operational costs sum to the variable operational costs a fuel cost of 85 €$/MWh$, of which value is retrieved by the work of Koirala et al. (2021). This assumption allows the biomass power plants to be dispatchable and with a firm capacity correspondent to the installed capacity, ensuring their reliable operation within the system and allowing them to participate in the electricity capacity market (Φ is set to 1 in Equation (4.8)).

Hydrogen-fired turbines, namely thermal generators that use hydrogen as fuel, represent the other flexible units of the system and rely on the hydrogen sector for hydrogen availability. The latter is however a market result, which should coordinate investment in generation capacity and ensure that this capacity is efficiently used. In this project, only open-cycle hydrogen turbines are considered.

Hydrogen-fired turbines are comparable to gas-fired turbines for characteristics such as easy activation, low capital costs and high operational costs and their role as peak or backup units (IEA, 2019). However, if blending hydrogen with gas and using it to fuel a gas turbine is already possible by adapting the latter, pure hydrogen-fired turbines are a new concept still in their development phase and their specifications are less clear (Hernandez & Gençer, 2021). However, as the industry evolves, it is legitimate to assume that hydrogen turbines will exhibit a cost structure comparable to that of conventional natural gas power plants. Lux & Pfluger (2020) provide reasonable assumptions about the future costs of hydrogen-fired turbines, considering the turbine capital cost and the non-fuel variable cost. As the fuel cost is endogenously determined by the model, as is the amount of fuel needed, it is not included in the cost structure but it is explicitly added to the objective function (Equation (4.19)). The different considerations of fuel cost between biomass and hydrogen could be trivial looking at Table 5.1, but endogenously determining the hydrogen cost is crucial as it is triggered by sector coupling dynamics, and at the same time triggers them.

Turbines' conversion efficiency, namely the ratio between the output and the energy content of the hydrogen in terms of Lower Heating Value (LHV), is set at 40% (Lux & Pfluger, 2020). It is assumed a constant efficiency with the power output and that there is no time delay between the purchasing and the consumption of hydrogen.

An overview of the costs and technological parameters of the power generators is presented in Table 5.1.

Table 5.1: Overview of costs and technical parameters of electricity suppliers

Technology	Overnight Costs [M€/GW]	Operational Costs [€/MWh]	Lifetime [yr]	Efficiency [-]
Solar	529	2	35	/
Wind Turbines	1118	5	25	/
Biomass	4400	85 (including fuel)	25	/
H2 Turbines	450	2.7 (excluding fuel)	30	0.40

Similarly to hydrogen-fired turbines, hydrogen supply technologies are surrounded by uncertainty about their costs.

Electrolysis is a well-known process, which however needs to be intensively studied to reduce the high capital costs and improve the low efficiency of the technologies in order to become competitive (Lux & Pfluger, 2020). There are currently three main technologies in water electrolysis: Alkaline Electrolysis (AEL), Polymer Electrolyte Membrane Electrolysis (PEMEL) and Solid Oxide Electrolysis (SOEL). While SOEL is still in its pre-commercial stage, AEL is the most mature in the market at the moment. However, it is expected that in the long term, PEMEL will achieve similar costs to AEL, with the advantage of having the most flexible operation and, therefore, being the most suitable one to be powered by fluctuating renewable power (Lux & Pfluger, 2020). The model does not differentiate between electrolyzers technologies, therefore only one agent for electrolyzers is included. Parameters' values refer to the AEL technology, which here exhibits overnight costs equal to 500 $M€/GW_e$.

Electolyzers' capacity is expressed in the model in terms of electricity input. Variable costs for maintenance and water are neglected, while the electricity cost is explicitly part of the objective function and it is endogenously determined. The amount of hydrogen production is linked to the electricity input by the electrolyzers' efficiency, which is optimistically assumed at 68% and is defined as the ratio between the electricity consumption and the energy content of the hydrogen produced. The efficiency is assumed constant with the output.

With regard to hydrogen long-term storage assets, salt caverns have been selected as the most promising solution. Indeed, gas-depleted fields are still surrounded by uncertainty, while liquid hydrogen storage in tanks is less suitable for long-term storage purposes (IEA, 2019; Groenenberg et al., 2020). Salt caverns are associated with a long lifetime; however, their costs are mainly driven by the auxiliary technologies that allow the transportation and treatment of the gas. Transportation costs are neglected. According to a recent study by TNO (Groenenberg et al., 2020), underground hydrogen storage in salt caverns has an overnight investment cost structure composed of costs related to the cavern itself equal to 150 $€/ton_{H_2}$, costs for the compressor and dryer equal to 4200000 $€/ton_{H_2}/h$, and costs for the expander gas treatment equal to 2520000 $€/ton_{H_2}/h$. These costs are converted in $M€/GW$ and $€/MWh$ by using the hydrogen LHV (33 MWh/ton_{H_2}). Operational costs of the salt cavern storage plant are neglected.

The modelling of technological constraints is highly simplified. According to Groenenberg et al. (2020) and Michalski et al. (2017), storage in salt caverns presents high efficiency. In this work, the charging efficiency represents the efficiency of the compressor and includes its electricity consumption. Similarly, the discharging efficiency refers to the expander and gas treatment section and accounts for their electricity consumption. Their electricity consumption is assumed in the order of 1 MWh_e/ton_{H_2} (Michalski et al., 2017; Groenenberg et al., 2020). To include this loss in their efficiency, the electricity consumption is converted into the energy content of the hydrogen that could have been produced via electrolysis with the same amount of electricity. The calculation of the efficiency is then straightforward, dividing this term by the hydrogen LHV. Charge and discharge efficiencies result to be equal to 95%.

The following table presents the selected parameters of hydrogen sector technologies.

Table 5.2: Overview of costs and technical parameters of hydrogen suppliers

Technology	Overnight Costs	Operational Costs [€/MWh]	Lifetime [yr]	Efficiency [-]
Electrolyzers	500 $M€/GW_e$	/	25	0.68
Salt Cavern Storage	206 $M€/GW_{H_2}$ 150 $M€/TWh$	/	40	charge: 0.95 discharge: 0.95

Most of the energy losses of the hydrogen sector, therefore, lie in the electrolysis step (where only 68% of electricity is converted into hydrogen) and, eventually, in the reconversion to electricity by means of the hydrogen-fired turbines. On the other hand, charge and discharge efficiency, which ultimately refers to the compressors' and gas expanders' capacity, are higher (95%) than electrolysis and hydrogen turbines, while transportation losses are neglected, as transportation is not explicitly modelled.

5.2. Demand Characterization

As introduced, external demand agents are considered aggregately and price-elastic up to a price cap. The price cap is represented by their willingness to pay, which allows quantifying the consumers' utility in monetary terms. WTP is set to 1000 €$/MWh$ for both the electricity and hydrogen sectors.

As introduced in Section 3.2 and illustrated in Figure 3.2, the price elastic demand function is made by two sections, the first one characterized by a constant WTP and the second one represented by a sloped curve. Both sections introduce price elasticity, but in a different way: the sloped section allows voluntary adjustment of the served demand as a function of the energy price, while the constant WTP section allows for involuntary curtailment whenever the price cap is reached. Even if the demand is endogenously determined, it is necessary to have a demand input to define the consumers' utility function. In particular, the demand input characterizes the constant WTP section and the elastic section.

The function is built up as follows. The constant WTP section is defined as up to 80% of the historical electricity demand (setting ψ as 0.8 in Constraint (4.55)). However, the last section of the function is defined as price-elastic. The price-elastic section is mathematically represented by a sloped function, which is obtained for the electricity demand by interpolating the function in two points. One consists of the limit of the constant WTP section, taken at 80% of the historical demand, and the WTP value. The second point is obtained by historical electricity demand and price. The slope m is then calculated for the electricity demand function as:

$$m = \frac{\lambda_t^{e,hist} – WTP}{D_t^{e,hist} – 0.8 \cdot D_t^{e,hist}} \tag{5.2}$$

where $\lambda_t^{e,hist}$ is the historical hourly electricity price and $Dt^{e,hist}$ the historical hourly electricity demand. Historical data for the electricity demand and prices of the Dutch area are retrieved from ENTSO-E open database for each year between 2017 and 2022.

The width of the elastic section can then be calculated from the price elasticity by dividing the WTP by the slope coefficient m. The elastic section is what allows to express price elasticity in the consumer optimization problem. The consumers' surplus represented in Figure 3.2 is translated into the term of the consumers' utility function within the square brackets of Equation (4.58) by applying a simple geometrical proportion.

For the hydrogen demand, the slope is not calculated from historical data as a green hydrogen market does not exist yet. Instead, hydrogen price elasticity is assumed to be constant and equal to the calculated average price elasticity of the Dutch electricity demand.

It is important to note that the definition of the price elasticity for the hydrogen demand based on electricity data does not necessarily represent the real conditions of the market, as at the moment of writing a market for green hydrogen does not exist yet. This does not affect the validity of the results but entails paying attention when setting the hydrogen demand WTP, as it is not directly correlated with the exogenously determined (from electricity data) price elasticity. If the WTP is too high, the elastic section could become very extended, allowing an unrealistic price elasticity. On the other hand, a too-low WTP could lead to a scenario where the hydrogen theoretical demand would be greater than the one represented on the curve. This justifies the choice of using the same WTP for electricity and hydrogen. In order to avoid possible negative prices, the elastic term of the demand $e^{ela}_{co,dt}$ is constrained to be smaller than the elastic section $D^{e}_{ela,dt}$, as visualized again in Figure 5.1. Constraint (4.56) and Constraint (4.62) are here repeated, and ensure the latter concept is applied to all the scenarios:

$$0 \le e^{ela}_{co,dt,y} \le D^{e}_{ela,dt,y} \qquad (\underline{\mu}^{ela}_{dt,y}, \overline{\mu}^{ela}_{dt,y}) \qquad \forall d,t,y \tag{5.3}$$

$$0 \le h^{ela}_{co,dt,y} \le D^{H_2}_{ela} \qquad (\underline{\mu}^{ela,H_2}_{dt,y}, \overline{\mu}^{ela,H_2}_{dt,y}) \qquad \forall d,t,y \tag{5.4}$$

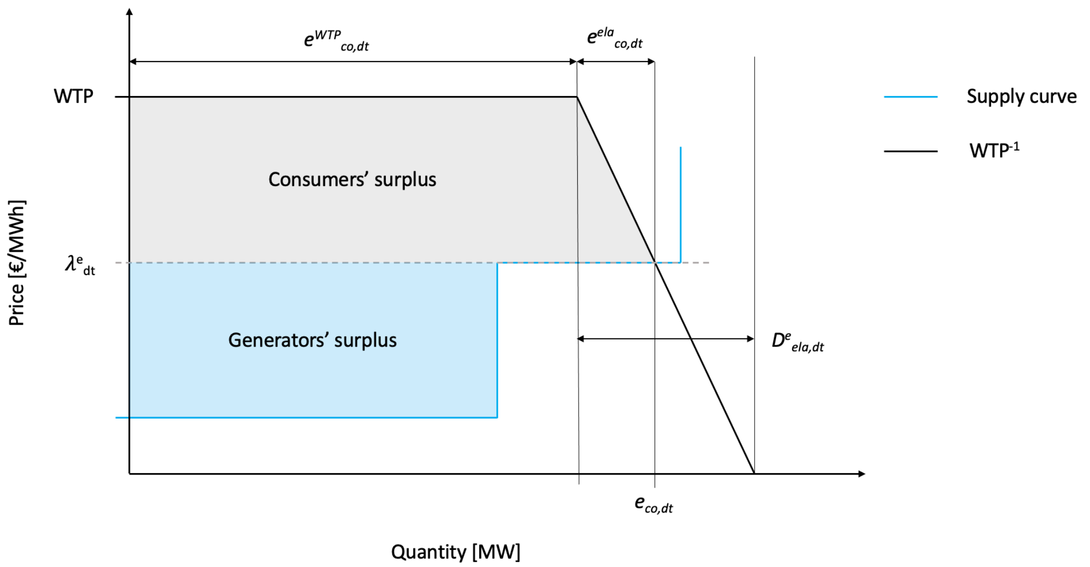
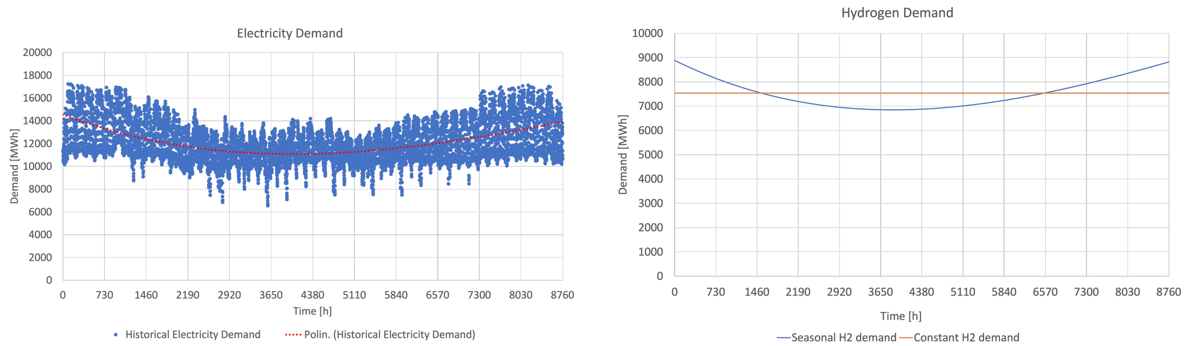


Figure 5.1: Inverse willingness-to-pay and supply functions

Given the uncertainty surrounding the future demand for green hydrogen, a reference target of 50 $Mton$ of hydrogen per year has been set to meet the decarbonization targets at the European level. This target is based on the REPowerEU plan (European Commission, 2022), which estimates 20 $Mton$ of annual demand by 2030, and is increased by a factor equal to 2.5 to represent an expected exponential growth in the long term as presented in (Alvik & Onur Özgün et al., 2022). The Dutch demand for hydrogen is estimated to account for approximately 4% of the total European hydrogen demand, resulting in an annual demand of 2 $Mton$ of hydrogen. The assumption on this share is based on considering the Dutch electricity demand share in Europe as a fraction of the European electricity demand.

The external demand agent does not include the demand from hydrogen-fired turbines, which is calculated endogenously as in turn, they act as a demand agent themselves.

Similarly to what happens to the electric load, demand for hydrogen will likely follow a seasonal trend, with winter characterized by peak hydrogen and electricity demands. To model this, the constant hourly demand for hydrogen, obtained by dividing the annual demand by the hours of the year, is normalized and correlated to the interpolated electric load. This is presented in Figure 5.2 and ensures that the hydrogen demand has a seasonal trend while the annual demand remains constant. As for the electricity load, the hydrogen demand is met on an hourly basis and does not allow for potential inherent flexibility by, e.g., relaxing the matching on a daily basis.



(a) Electricity demand of the Netherlands (2021) - The hourly demand (blue dots) is interpolated to obtain the seasonal trend (red dots)

(b) Hydrogen demand - The projected uniform demand is correlated with the electricity demand seasonal trend to represent the stress situation for the whole system

Figure 5.2: Representation of the electricity demand (a) and the hydrogen demand (b) for the 2021 weather year

With regard to the demand for capacity cleared by the capacity market, it is widely known how setting the correct target is crucial but at the same time extremely difficult (De Maere d'Aertrycke et al., 2017). Therefore, the social optimal capacity calculated ex-ante in the risk-neutral simulation for the EOM design is used for the target capacity demand, following the approach used by Kaminski et al. (2021). This outcome is indeed the spontaneous optimal reached in case of perfect competition and should be, in theory, the objective pursued.

Considering the reasoning behind the capacity demand requirement for firm capacity presented in subsection 3.2.2, the capacity target is set differently for the electricity market and the hydrogen market.

The electricity capacity market considers only an exogenous inelastic demand for capacity, of which the target is simply the optimal dispatchable installed capacity for the risk-neutral case, as vRES generators are excluded from the market.

On the other hand, the hydrogen capacity market has in hydrogen-fired turbine generators a demand agent, which requires a certain amount of firm capacity to ensure that the capacity offered to the electricity sector is always available. The results in terms of electrolyzers and storage discharge capacity obtained from the risk-neutral setup refer to the total demand for hydrogen, which includes the external exogenous demand and the fuel demand from hydrogen turbines. As the latter require a firm capacity which is equal to the amount of electricity capacity offered in the electricity capacity market corrected by their efficiency, the target demand for hydrogen supply capacity is set at the social optimal of the risk-neutral case minus the optimal installed hydrogen-fired turbine capacity. By doing this, capacity costs are spread among agents and not only final consumers, as the hydrogen turbine's agent must pay for the additional capacity it is requiring. This allows for a more fair distribution of the costs.

5.3. Uncertainties within Scenarios

The model introduces uncertainty by incorporating discrete scenarios in the stochastic model. Each scenario is associated with a probability that influences its weight in the objective function. As they represent historical years linked with different scales of hydrogen demand, scenario probabilities follow a uniform distribution, assuming that all scenarios have equal probabilities.

A total of 18 scenarios are considered, which have been developed using a specific approach. Initially, six weather years for the Netherlands have been selected from ENTSO-E, from 2017 to 2022.

These years are characterized by the availability of wind and solar generators, as well as the electricity load.

Each of these six weather years obtained from ENTSO-E has been utilized to generate two additional scenarios, introducing uncertainty in the hydrogen market size. Consequently, each weather year is associated with three scenarios representing different levels of hydrogen demand: the reference demand, an increased demand by 20%, and a decreased demand by 20%. The reference hydrogen demand has been computed in Section 5.2.

To summarize, each scenario is distinguished by the electricity load, hydrogen load, and availability of solar and wind generators.

5.4. Market Designs

The model presented consists of the different generators and demand agents which participate in an integrated hydrogen and electricity market. This is strictly interdependent due to the interconnection represented by the sector-coupling technologies, i.e. electrolyzers and hydrogen-fired turbines. The formulation of the model elaborated in Chapter 4 represents the most complex and complete case; however, the analysis will be conducted for different market designs which refers to partial versions of it.

The market designs analysed are the following, presented with an increasing degree of complexity and summarized in Table 5.3:

- **Energy-Only Markets (EOM)**: this design includes the wholesale markets for electricity and hydrogen and does not include any capacity market. This is obtained by adapting the singular optimization problems of the agents, removing any term related to the offered and demanded capacity in the objective functions of the agents and neglecting the related constraints. Furthermore, the market clearing constraints for capacity (Equation (4.68) and Equation (4.69)) are not considered. This market remunerates agents only for the energy offered on an hourly basis to the market to match energy supply and demand.

- **EOMs supported by an electricity capacity market for dispatchable generators (CM E)**: this design adds to the wholesale EOMs an electricity capacity market for dispatchable generators, which remunerates the contracted capacity on a yearly basis. The problem presented in Chapter 4 is therefore adapted by neglecting the capacity terms in the objective functions and the related constraints for the electrolyzers, hydrogen storage and hydrogen demand agents, and does not consider the market clearing constraint for hydrogen capacity (Equation 4.69). Additionally, the hydrogen-fired turbine agent (referring to subsection 4.2.2) is not allowed to express a demand for hydrogen capacity anymore, but it offers its installed capacity to the electricity capacity market. The objective is to understand the eventual necessity of firm capacity for the hydrogen sector, as the capacity offered would be dependent on fuel availability.

- **EOMs supported by an electricity capacity market and a hydrogen capacity market (CM E+H2)**: this case refers to the integral formulation presented in Chapter 4. Here, the hydrogen turbine's agent additionally expresses a demand for firm capacity in the hydrogen capacity market to ensure the reliability of what they offer in the electricity capacity market. Electrolyzers and hydrogen storage can offer their capacity to meet the demand without requiring firm capacity in the hydrogen sector. On the other hand, storage volume and availability are not remunerated by the capacity market.

Table 5.3: Setting of the simulations for the different market designs.

Design	Markets	Target capacity demand	Weight mean-risk	CVAR interval
EOM	electricity EOM, H2 EOM	/	$\gamma = 0.5$	$\beta = [0.2 - 1.0]$
CM E	electricity EOM, H2 EOM, electricity CM for dispatchable generators	electricity CM: risk-neutral ($\beta = 1.0$) EOM optimum	$\gamma = 0.5$	$\beta = [0.2 - 1.0]$
CM E+H2	electricity EOM, H2 EOM, electricity CM for dispatchable generators, H2 CM	electricity CM: risk-neutral ($\beta = 1.0$) EOM optimum H2 CM: risk-neutral ($\beta = 1.0$) EOM optimum	$\gamma = 0.5$	$\beta = [0.2 - 1.0]$

6
Results

The main findings of the simulations are presented in this chapter. To answer the question of the market design's suitability to attract adequate investments in hydrogen capacity for an integrated and decarbonized hydrogen and electricity system in the presence of risk-averse investors, the impact of risk aversion on the three proposed market designs (EOM, CM E, CM E+H2) is studied. The metrics used to evaluate the effects of the level of investment combine the system adequacy perspective and the cost perspective.

The chapter is structured as follows. Section 6.1 presents the equilibrium reached when risk-neutral agents are driven by an EOM, with the aim of explaining what the model is able to provide and defining a benchmark optimal case. After this, in Section 6.2 the effect of risk aversion is compared with the benchmark to show the functioning of the system. The analysis proceeds in Section 6.3 with a more general overview of the effect of risk aversion on the performance of the three proposed market designs. This section focuses on the effect of potential deviation in installed capacity and what this entails in terms of energy served and market prices. Furthermore, the analysis is completed by analysing costs of energy, profits and social welfare from the different actors' perspectives to study possible transfers of welfare. Lastly, Section 6.4 provides insights on the effect of fixing the vRES capacity to the optimal level and how this influences energy prices and the strategy of the other agents.

6.1. Model Performance for the EOM

The long-term equilibrium for an EOM driven by risk-neutral agents' strategies results in a socially optimal capacity mix which serves as a benchmark case for the comparison of performances of the different market designs. Referring to the problem formulation of Chapter 4, this corresponds to expressing the agents' problems for EOM with a $\beta = 1.0$ or, alternatively, to set $\gamma = 1.0$. In this way, the strategy of each agent is only based on the expected profit.

Referring to the electricity sector, investments for a total installed capacity of 150.58 GW have been made. As visualized in Figure 6.1, the electricity capacity mix is primarily composed of variable renewable energy sources (vRES), which account for 93% of the electricity generation capacity. Among the vRES, solar PV and wind energy share an almost equal proportion. The remaining 7% of the capacity is comprised of dispatchable sources, specifically 7.51 GW of biomass capacity and 2.52 GW of hydrogen-fired turbine capacity. These dispatchable sources play a crucial role in fulfilling the electricity demand during periods when additional power is required to meet the residual load.

Compared to the current total generation capacity in the Netherlands and considering the electricity demand refers to historical data, the installed capacity could seem excessive. However, there are two justifications for such a high capacity. Firstly, the high share of vRES requested in the decarbonized energy system comes along with their uncertain availability, therefore their firm capacity consistently differs from the installed one. To compensate for this variability, a higher installed capacity is necessary to ensure a reliable and consistent electricity supply.

Moreover, the demand for hydrogen stimulates investments in electrolyzer capacity, reaching 33.04 GW_e. Hydrogen production creates a significant additional electricity demand, which on average is equal to an additional hourly demand of 14309 MWh. This is in the order of the external electricity demand. It is important to recall that hydrogen storage allows the decoupling of hydrogen production and supply. The additional hydrogen demand for electricity is therefore not constant, and it is concentrated in those periods of high vRES generation.

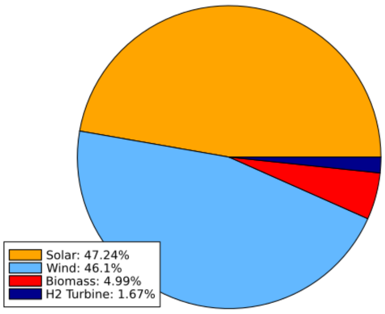


Figure 6.1: Electricity capacity mix - Technology shares

Technology	Installed Capacity [GW]
Wind	69.41
Solar PV	71.14
Biomass	7.51
H2 turbine	2.52

Figure 6.2: Electricity installed capacity in absolute values

As can be seen in Figure 6.3, the hydrogen capacity mix is balanced, with the capacity of electrolyzers exceeding the storage discharge capacity by 8 GW. This is justified by the fact that the former are the hydrogen producers, and storage is ultimately dependent on electrolysis to stock hydrogen. To ensure coherence, the electrolyzer capacity is converted into hydrogen output capacity when compared to hydrogen storage.

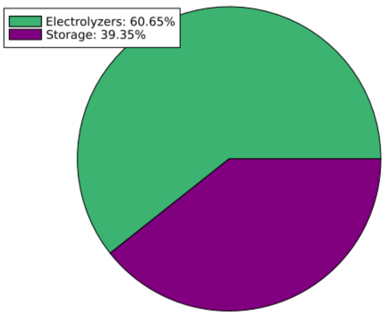


Figure 6.3: Hydrogen capacity mix - Technology shares

Technology	Installed Capacity [GW]
Electrolyzer	33.04 GW_e - 22.47 GW_{H_2}
H2 storage	14.57 GW_{H_2}

Figure 6.4: Hydrogen installed capacity in absolute values

To complement the charge and discharge capacity, investments have been made in a storage volume of 11.44 TWh. This enables a potential availability of 32 days of discharge at the maximum rate when storage is fully charged. This is coherent with the role of salt caverns, which are modelled as long-term storage facilities and have the role of dampening seasonal variations and potential backup for long periods without vRES availability. The initial SOC of the day is plotted for the whole year and for each scenario in Figure 6.5, confirming the seasonal behaviour of hydrogen storage deployment.

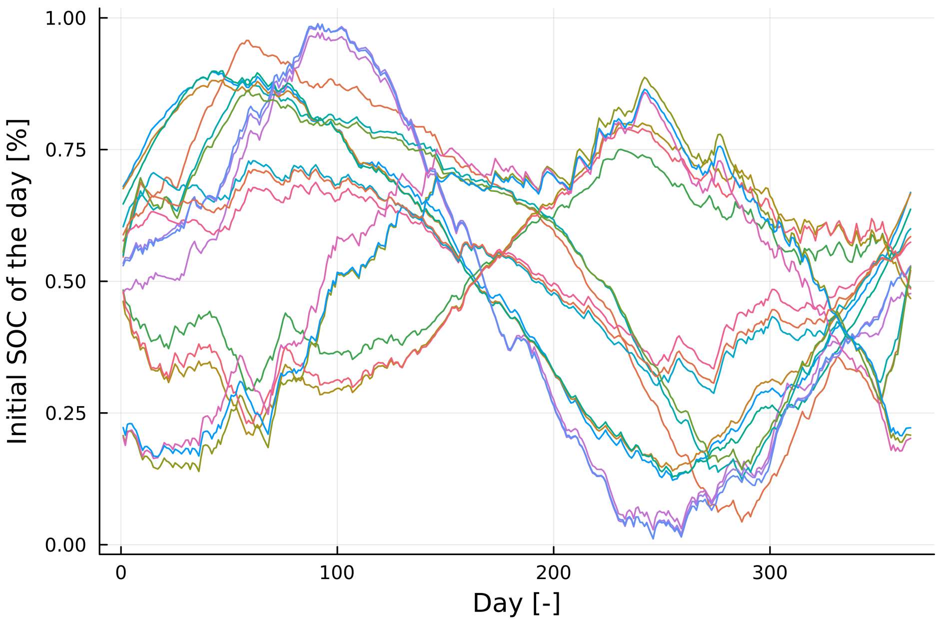


Figure 6.5: SOC of hydrogen storage at the beginning of each day for the 18 scenarios

From the figure above it can be concluded that no common seasonal effect regulates the charge and discharge of hydrogen storage, as the profiles are reversed for some years. This is possible as the different years are not modelled as consecutive, but represent discrete scenarios whose possibility is considered and influences the strategy of the agents, therefore there is no constraint between the final SOC of one year and the initial SOC of the following one. The different profiles, however, are a result of the vRES availability of particular years. Here, 2019 and 2021 present the SOC peak in the second half of the year, contrary to the other years which show it during the first half.

As presented in Section 4.2, each agent takes a unique decision on the capacity to invest based on the optimization by considering the weight of the different scenarios. Hence, wholesale energy prices are defined for each scenario. To analyze the price duration curves, representative days prices are extended to the whole year by considering their weight. The average price duration curve is then computed by averaging the hourly price duration curves of all the scenarios.

Figure 6.6 presents the average electricity hourly price duration curve. The first thing that can be noticed is that, compared to the price duration curve of 2022 for the Netherlands, electricity prices are lower in the modelled energy system. This is always true apart from the very last few hours of vRES surplus, which in the real world correspond to negative prices, while the modelling approach of the demand does not allow them. In general, electricity prices are driven downward by the very high share of vRES. The latter, however, recover their costs (compare the risk-neutral case in Figure 6.10). The average electricity price is 122.89 €$/MWh$, while the median electricity price is 85.12 €$/MWh$. The sustained low prices periods visualized on the flat region at the centre of the curve, which account for more than 80% of the year, come with the downside of having more unexpected price spikes, which however in this case are limited in magnitude and frequency as agents are considered risk-neutral.

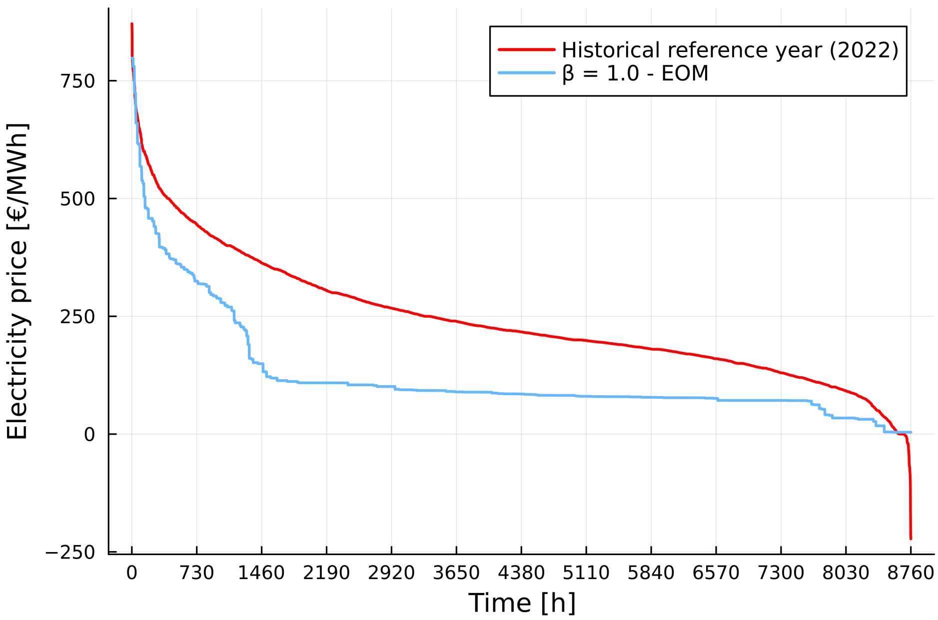


Figure 6.6: Electricity hourly price duration curve for the risk-neutral case

Even though it presents the vRES-induced flat region, the obtained electricity hourly price duration curve has a shape similar to the real-world curve of 2022. In particular, despite the very high share of vRES, prices are remarkably meaningful, avoiding zero prices. This leads to the important conclusion that, in the modelled decarbonized system reliant on vRES generators, marginal pricing allows to have a market outcome where generators can recover their cost via the market.

By using the same approach, the hydrogen hourly price duration curve is obtained and presented in Figure 6.7. Hydrogen price here varies between approximately 3 and 7 €$/kg$, with an average of 4.14 €$/kg$. The latter is slightly higher but in line with the average Levelized Cost of Hydrogen (LCOH) forecasted for 2030 in the EU for grid-connected electrolysis hydrogen, which is expected to settle around 3.8 €$/kg$ (Alvik & Onur Özgün et al., 2022).

The first thing that stands out is the fluctuating behaviour of the hourly hydrogen price. A first explanation of this behaviour lies in the fact that the system is modelled without the possibility to import or export energy but the model requires that demand and supply are matched hourly. Furthermore, combining the limited price elasticity of the external hydrogen demand with the fluctuating electricity prices that electrolyzers face in the electricity market, the hydrogen market clearing results in fluctuating prices, which evidently cannot be dampened by the - limited - storage, which however presents generational costs.

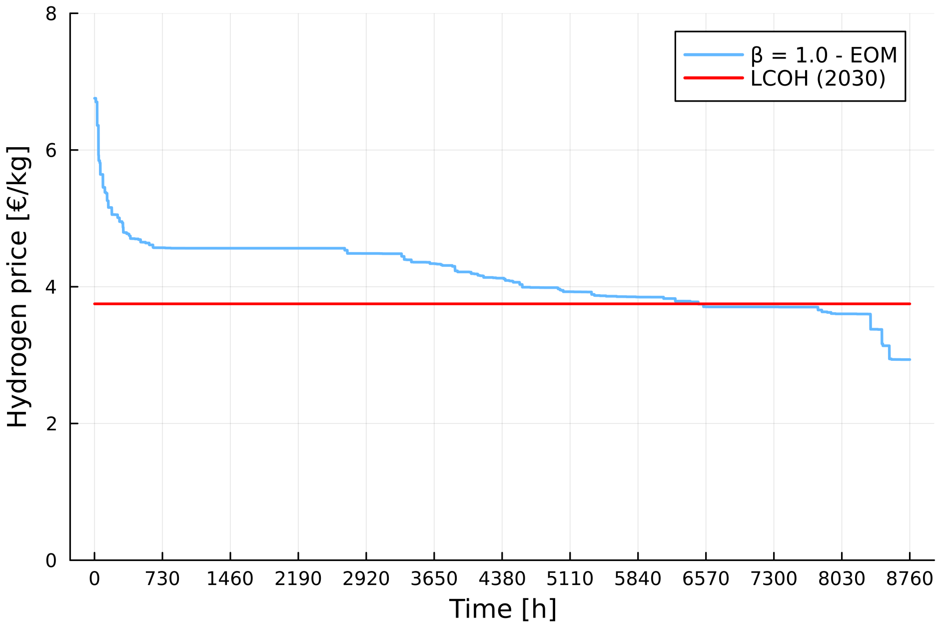


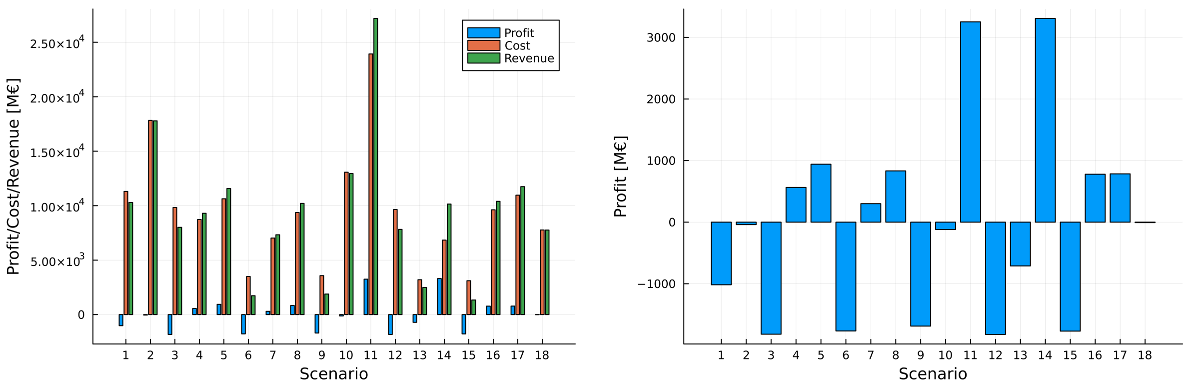
Figure 6.7: Hydrogen hourly price duration curve for the risk-neutral case

As explained, each scenario differs in input and, therefore, in the operational decisions of the actors. This will lead to differences across scenarios in the volume of energy offered by each actor and in the clearing prices they are exposed to. Consequently, profits can highly differ across scenarios.

Considering, for example, the electrolyzer technology, the differences across scenarios in terms of costs, revenues and profits are presented in Figure 6.8(a). They are mainly driven by the variation of demand that they have to fulfil, electricity prices dependency on power generators' availability and periods and rate of deployment of electrolyzers, which in turn can compete with hydrogen storage.

As introduced, risk-neutral agents choose their strategy based on the expected profit, calculated as the sum of each scenario profit Π_y weighted by its probability P_y. Figure 6.8(b) focuses on the differences in terms of profit across scenarios. In this case, the yearly expected profit (Equation (4.21) with $\gamma = 1$) for the electrolyzers' agent amounts to 0.084 million €, which is 5 orders of magnitude lower compared to the scenario with revenues (1341.837 million €). As expected, in a perfect market with risk-neutral agents, investors do not recover any long-term profit.

However, when agents become risk-averse, uncertainty in profits makes them require a risk premium to invest, which results in expected revenues that exceed expected costs.



(a) Comparison of profits, costs and revenues

(b) Focus on profits

Figure 6.8: Profits, costs and revenues of each scenario for the electrolyzer technology when it is assumed risk-neutral - Each scenario has the same weight in computing the expected profit and orienting investments

6.2. The Effect of Risk Aversion: Insights into the Model's Mechanics

As presented in Section 3.2, modelling risk-averse agents by means of CVAR allows to consider the worst-case scenarios defined by the parameter β. Agents adapt their strategy by requiring a risk premium that allows them to recover their cost even if hey experience only the selected worst scenarios, protecting themselves from this probability. The risk-averse agent's problem is adapted by setting β to a value smaller than one (recalling the lower the β, the higher the degree of risk aversion).

In the risk-averse set-up of the model, the resulting expected profit corresponds to the risk premium required by the risk-averse agents to protect themselves against the worst-case scenarios. This, in general, increases with the degree of risk aversion.

Figure 6.9 visualizes the objective function result of the risk-averse electrolyzers' agent in the EOM case for a $\beta = 0.3$. Profits are ordered on the x-axis in increasing order from the worst case to the best case. The y-axis shows the scenarios' probabilities, which are all equal to 5.56% as assumed uniformly distributed.

The expected profit is in this case 1250.41 million € per year and cannot be considered negligible anymore. The CVAR term is calculated considering the scenarios with a cumulative probability equal to β, in this case, the 5 worst scenarios [1], and has a value of -1251.73 million €. It is therefore clear how the CVAR term coincides with a risk premium requested by the agent to overcome possible adverse scenarios.

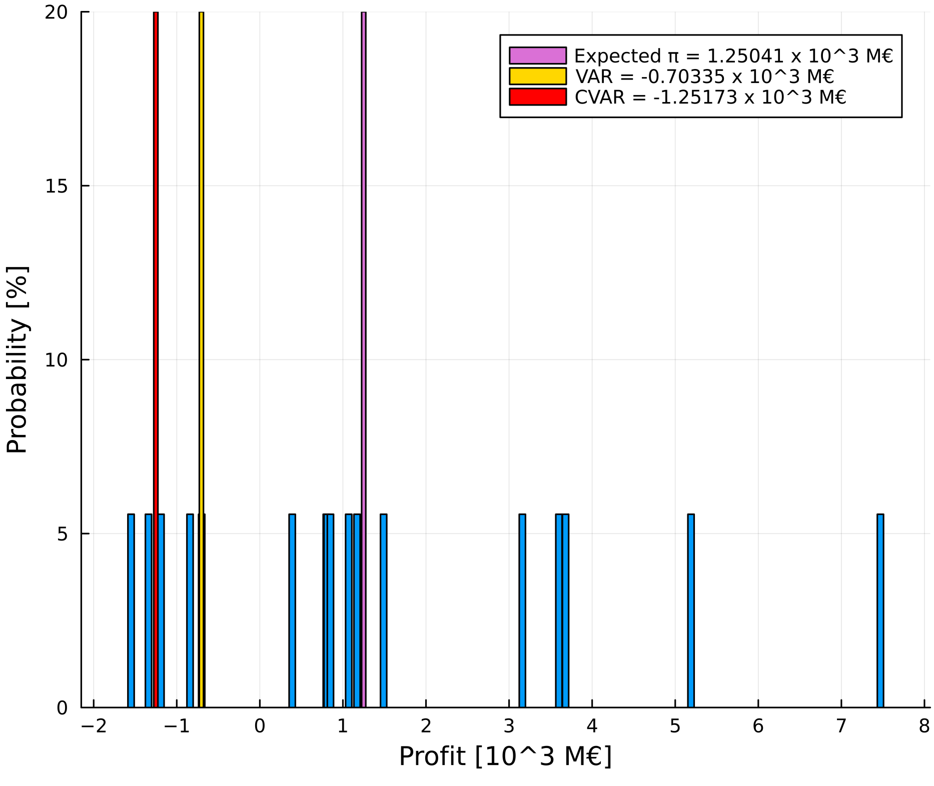


Figure 6.9: Decomposition of the objective function results for the risk-averse electrolyzers' agent - The profit distribution is presented together with the expected profit, the VAR and the CVAR

[1] It is important to note that, as the distribution is discrete and the β used does not coincide with the cumulative probability of the distribution, the computation of CVAR with the linearized reformulation slightly differs from the theoretical definition of CVAR, as the former computes a linear approximation. This has been studied to validate the CVAR formulation. However, the linear approximation does not affect the validity of the results, as the effect on the objective function is the same.

Figure 6.10 shows the expected profit for the different generation technologies under different market designs and degrees of risk aversion; by comparing the first two columns it can be seen how all the agents increase the risk premium required by acting risk-averse in an EOM. Furthermore, looking at the market designs that include capacity markets (dark blue and red bars), it can be seen how the required risk premium is reduced, highlighting how these markets allow to mitigate risk.

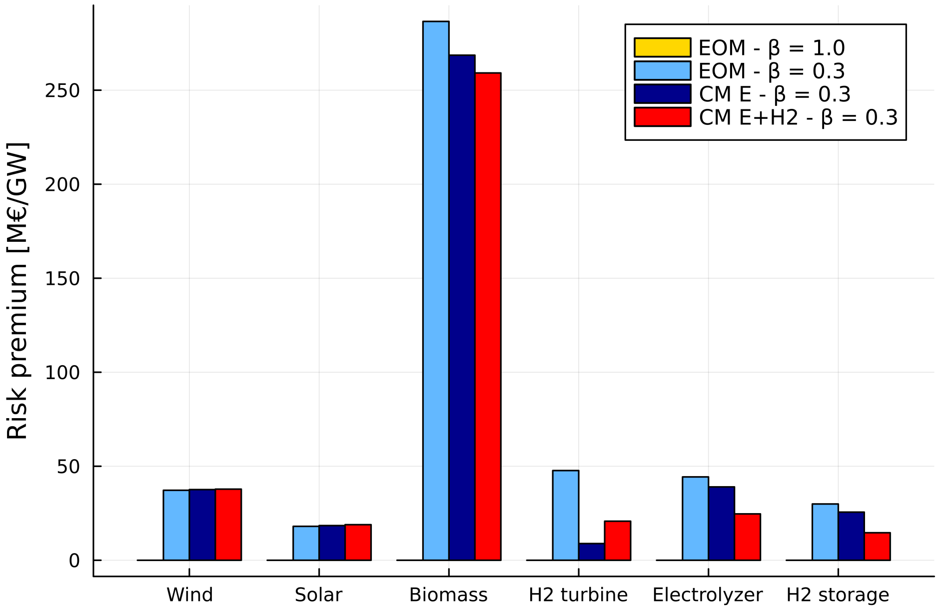


Figure 6.10: Expected profit (risk premium) of each technology in four different cases: EOM with risk-neutral agents, EOM with risk-averse agents, an EOM supported by a capacity market for electricity with risk-averse agents, an EOM supported by a capacity market for electricity and a capacity market for hydrogen with risk-averse agents

Risk aversion makes agents require a risk premium to recover their investment, affecting their strategies. In general, they reduce investment in capacity and require higher electricity and hydrogen prices to recover the risk premium. Consequently, the amount of served demand decreases (as it will be extensively discussed later in Section 6.3).

Figure 6.11 presents the installed capacity for each technology under different market designs and degrees of risk aversion. Comparing the bar for the risk-neutral EOM case (yellow) and the bar for the risk-averse EOM case (light blue), it can be seen that in an EOM increasing the degree of risk aversion results in a decreasing installed capacity. Only biomass does not reduce its installed capacity, as it is only exposed to uncertain electricity prices and therefore less risky. On the contrary, the other agents are dependent in terms of availability (e.g., vRES) and variable costs (e.g., electrolyzers, hydrogen storage, and hydrogen turbines), suffering from a reduction in installed capacity. Even though the risk premium required from biomass generators is high due to high capital costs, the independence of biomass availability and variable costs from uncertain parameters leads biomass to replace other power generators.

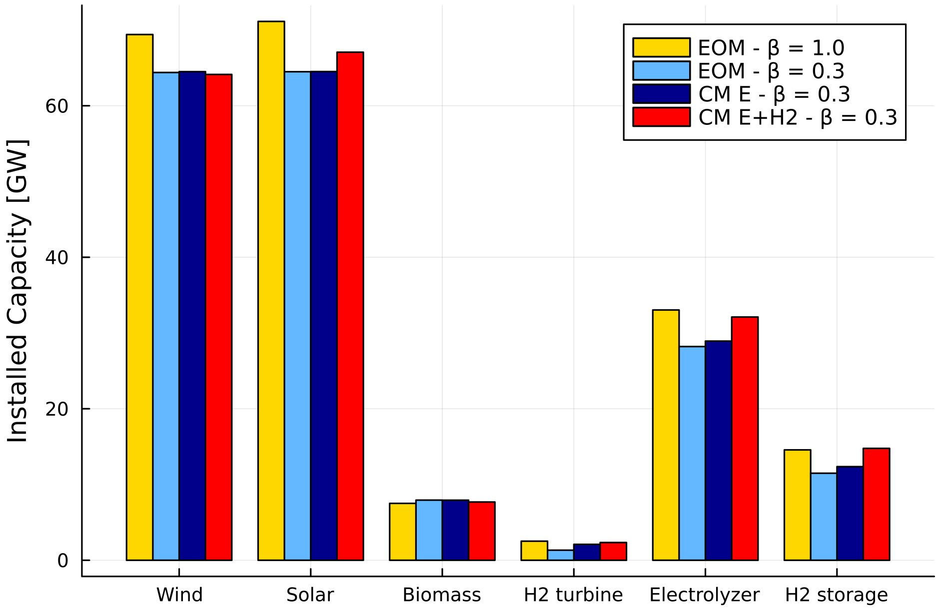


Figure 6.11: Installed capacity of each technology in four different cases: EOM with risk-neutral agents, EOM with risk-averse agents, an EOM supported by a capacity market for electricity with risk-averse agents, an EOM supported by a capacity market for electricity and a capacity market for hydrogen with risk-averse agents

The introduction of a capacity market for dispatchable electricity generators (bars in dark blue) is effective only for them, and just slightly restores electrolyzers and storage capacity. A possible market correction that could allow agents to hedge risk consists of supporting the EOM with both the capacity market for electricity dispatchable generators coupled with the capacity market for hydrogen capacity. By looking now at the red bars of Figure 6.11, it is possible to see how this adaptation promotes reestablishing the socially optimal capacity mix for the actors of both sectors. The revenues from the capacity market are independent of the scenarios and therefore represent a reliable income that encourages to install capacity and dampens risk aversion.

However, as vRES are excluded from the latter, they still reduce the installed capacity and increase their profit even more. The indirect effect of an increased electrolyzers' capacity and the consequent increase in hydrogen demand met make vRES more profitable, confirming Hesel et al. (2022) conclusion that vRES generators benefit from the increase in hydrogen generation capacity. Analysing the risk premiums for this market design by looking at the dark blue bars of Figure 6.10, it can be noticed how vRES are the only ones who see them increasing with the addition of capacity markets, while the others experience a reduction with respect to the EOM case with the same degree of risk aversion. However, long-term profits are still non-zero, as vRES reduction affects energy prices and, in general, all the generators benefit from this.

6.3. Trends and Comparative Analysis of Market Designs

After having presented the functioning of the model and what it is able to provide, the focus now is on the effect of risk aversion on the performance of the three proposed market designs. This evaluation will be conducted from a broader perspective, emphasizing a comparison based on selected indicators, rather than focusing on specific individual cases.

The initial focus will be on evaluating the impact of risk on the installed capacity within the proposed market designs, in order to gain insights on the interdependence of the two sectors.

In terms of generation adequacy, the first indicator used is the average amount of served energy. It is computed as the percentage of energy served with respect to the nominal demand and expressed by a duration curve. The nominal demand corresponds to the exogenous demand used to calibrate the inverse WTP function of the demand agents. The average amount of energy served can be calculated as:

$$\Delta D_{dt} = \sum P_y \frac{(e_{co,dt,y} - D^e_{dt,y})}{D^e_{dt,y}} \tag{6.1}$$

Flexibility measures such as the implemented price-elastic demand might, however, make the assessment of system adequacy more difficult. The flexible demand avoids shortages to some extent, as load shedding can happen only when the price goes over the WTP. For lower prices, the demand reduction does not necessarily represent unmet demand but rather demand not participating in a trade convenient for its utility function (Brito-Pereira et al., 2022). Instead, signals of lack of adequacy could manifest themselves with prolonged periods of high prices and, consequently, with excess reduced demand, more than the social optimal level (De Vries & Sanchez Jimenez (2022); Brito-Pereira et al. (2022)). This is particularly true in a system largely based on vRES as the one considered in this project. Therefore, a second analysis to assess system adequacy consists of the comparison of the shape of price duration curves.

Working with a stochastic model and with representative days requires an adaptation of the initial results. Price duration curves are obtained by extending the representative days' prices to the whole year by accounting for the weight of each day (i.e. it is assumed that the prices of each representative day will repeat as many times as its weight during the year). The obtained price duration sets are then averaged across the scenarios.

Considering the costs and benefits of the different market designs, the performances will be analyzed from a system perspective, where the total social welfare will be compared for the different cases and degrees of risk aversion. The total social welfare is measured as the sum of the expected profit of all the agents a:

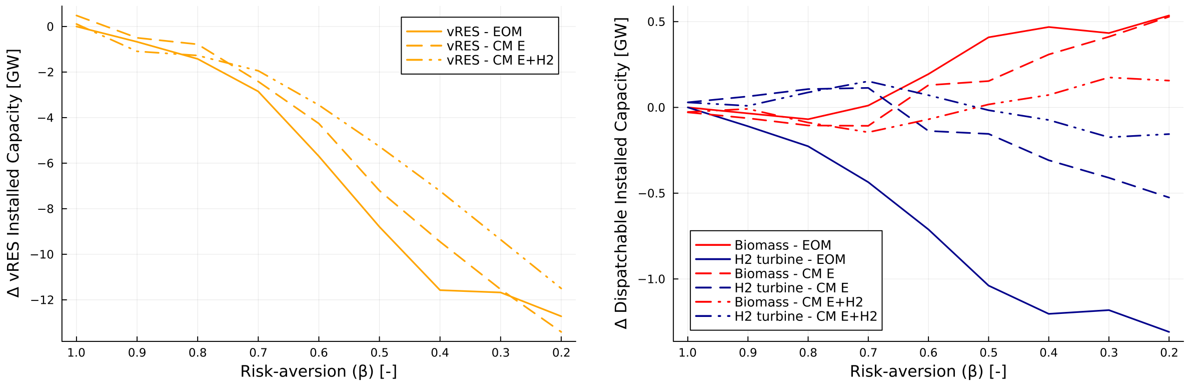
$$SW = \sum_a \sum_y P_y \Pi_{a,y} \tag{6.2}$$

Furthermore, to investigate potential welfare transfers, a comparison will be conducted between the profit of consumers and generators. Finally, the cost of energy for consumers and the producers' cost recovery are analyzed to explore individual agents' perspectives.

6.3.1. Impact on Investment

Risk aversion affects the agents' strategies by giving more importance to those scenarios with lower profits, discouraging investments in generation capacity as they might not be paid back. In an EOM, the total electricity capacity drops from 150.57 GW for the risk-neutral case to 137.06 GW for the risk-averse case where $\beta = 0.2$. Figure 6.12 presents the variation in installed capacity for vRES (Figure 6.12(a)) and dispatchable generators (Figure 6.12(b)) calculated as the difference between the installed capacity in the risk-neutral EOM case and the installed capacity in a particular market as a function of the degree of risk aversion β. [2]

[2] It is worth mentioning that, for the risk-neutral case, the capacity mix should not depend on the market design, as in principle there is no need for capacity remuneration. However, it can be noticed that the introduction of the electricity capacity market entails a slight variation in the vRES capacity, which is 0.4 GW higher in the last case. This is likely to be due to the tolerance of the EOMs, which is set as 0.1% of the energy demand, combined with the tolerance of the capacity market. As discussed, the choice of tolerance has been made by accounting for a trade-off between computational effort and the quality of the solution.



(a) vRES generators

(b) Dispatchable generators

Figure 6.12: Impact of risk aversion on electricity installed capacity in an EOM, EOM supported by a CM for electricity (CM E) and an EOM supported by a CM for electricity and a CM for hydrogen (CM E+H2)

Looking at the solid line in Figure 6.12, most of this decrease is ascribable to vRES installed capacity reduction, which combining wind and solar generation reduces up to 12.7 GW, equal to a 9% reduction. Clearly, the uncertainty of their availability combined with high capital costs affects their attractiveness.

As expected, the electricity capacity market, in which vRES do not participate, not even derated, does not correct the strategy of renewable generators, limiting the reduction in installed capacity of at most 2 GW with respect to the EOM design. On the other hand, the addition of a hydrogen capacity market indirectly makes vRES more profitable and dampens vRES capacity reduction, as a higher electrolyzer capacity introduces a higher peak electricity demand from the hydrogen sector. In this case, the reduction is dampened up to 4 GW, but it is still not enough to fully correct the effect of risk aversion.

Looking at the sub-figure above on the right, the dispatchable generation capacity is affected differently. Hydrogen-fired turbines, which in theory represent low-capital costs units, are deeply affected by risk aversion and see their installed capacity more than halved, with a decrease of 1.3 GW. On the other hand, biomass generators' capacity tends to replace the loss of hydrogen turbines by slightly increasing.

This conclusion is counter-intuitive when compared to the existing literature (see, e.g., Kaminski et al. (2021)): low-capital costs hydrogen turbines should benefit from high-risk aversion degrees when compared to capital-intensive biomass, which should suffer it. However, it must be taken into account how biomass and hydrogen-fired turbines are affected to different extents by uncertainties. Biomass generators have a variable cost which, even if it is relatively high compared to vRES, is fixed, and are exposed to risk only from the uncertainty of activation depending on electricity prices. On the other hand, hydrogen turbines are exposed to risk from two sectors: their use is strongly dependent on the volatile vRES generation availability, of which reduction increases electricity prices (Figure 6.18) and, indirectly, hydrogen prices (Figure 6.19). This indirect effect of risk aversion on hydrogen supply adds to the uncertain deployment of them, which, in the end, depends on electricity demand and vRES availability.

As can be seen, looking at the dashed lines, the introduction of a capacity market for dispatchable electricity generators is able to fix this bias towards biomass only for low degrees of risk aversion (i.e., high β), while for β lower than 0.7 only dampen the hydrogen turbine capacity reduction. However, the addition of the hydrogen capacity market seems effective in reestablishing a mix similar to the optimal risk-neutral: for any degree of risk aversion, the difference in the capacity of each technology with respect to the risk-neutral case does not exceed 0.18 GW. This is interesting considering that the hydrogen turbines' agent pays the hydrogen capacity price for the firm capacity demanded in the correspondent market, meaning that a hydrogen capacity market still benefits hydrogen turbines even if they have to pay for the firm capacity that is ensured. Figure 6.13 presents the costs for ensuring the firm capacity in the hydrogen capacity market (in orange) and the revenues from the offered capacity in the electricity capacity market (in blue). It is clear how the electricity market is more profitable, and revenues from it overcome the cost of the other, playing an important role in hedging risk and attracting adequate investment in hydrogen turbine capacity.

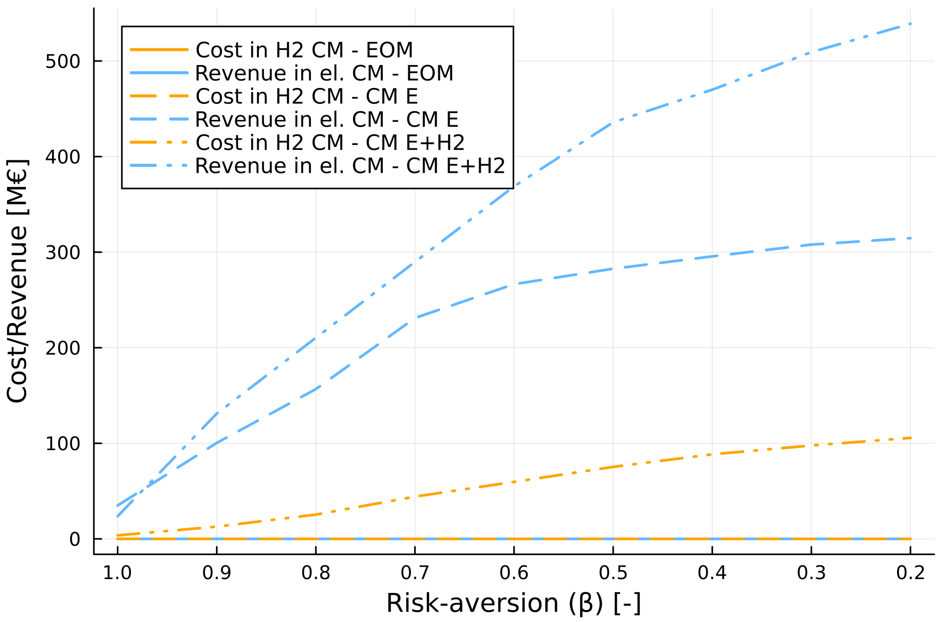
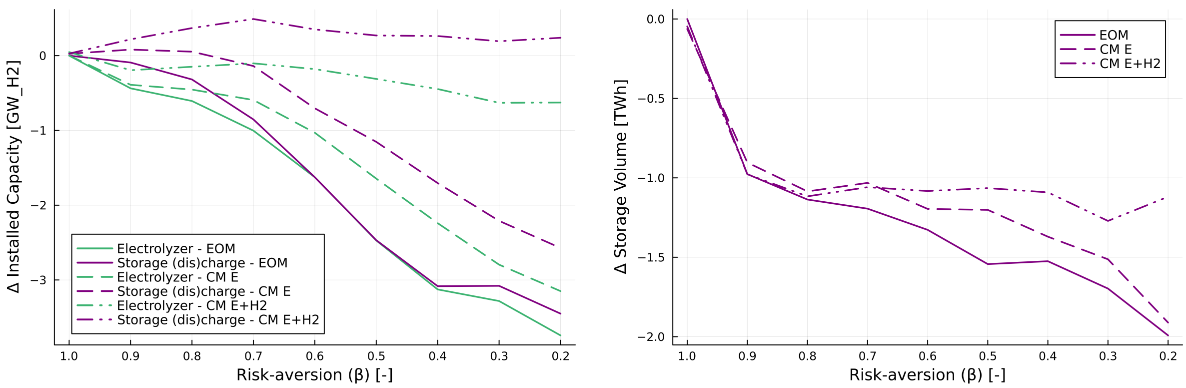


Figure 6.13: Comparison of costs for firm capacity in the hydrogen capacity market and revenues for the offered capacity in the electricity capacity market for the hydrogen turbine agent as a function of the degree risk aversion

The hydrogen capacity market is therefore beneficial for the electricity capacity mix: combined with an electricity market for dispatchable capacity it is able to partially correct the effect of risk aversion, reestablishing the dispatchable installed capacity and slightly dampening the reduction of vRES.

Focusing on the hydrogen mix, Figure 6.14 presents the variation in hydrogen generation installed capacity for (Figure 6.14(a)) and storage volume (Figure 6.14(b)) calculated as the difference between the risk-neutral value in the EOM case and the value for a particular market design as a function of the degree of risk aversion β.



(a) (b)

Figure 6.14: Impact of risk aversion on (a) hydrogen installed capacity and (b) storage volume in an EOM, EOM supported by a CM for electricity (CM E) and an EOM supported by a CM for electricity and a CM for hydrogen (CM E+H2)

As can be seen in the left subplot, both electrolyzers and storage capacities suffer an important reduction in the EOM case with an increasing risk aversion degree, respectively of 3.74 GW_{H_2} and 3.45 GW_{H_2}. These correspond to 17% and 24% with respect to the socially optimal levels. Accordingly, storage volume reduces from 11.44 TWh up to 9.45 TWh.

The first introduction of an electricity capacity market is beneficial for both technologies: the increase in hydrogen turbine capacity restores a higher demand for hydrogen from the electricity sector, stimulating investment in hydrogen capacity. However, the effect on storage volume is negligible.

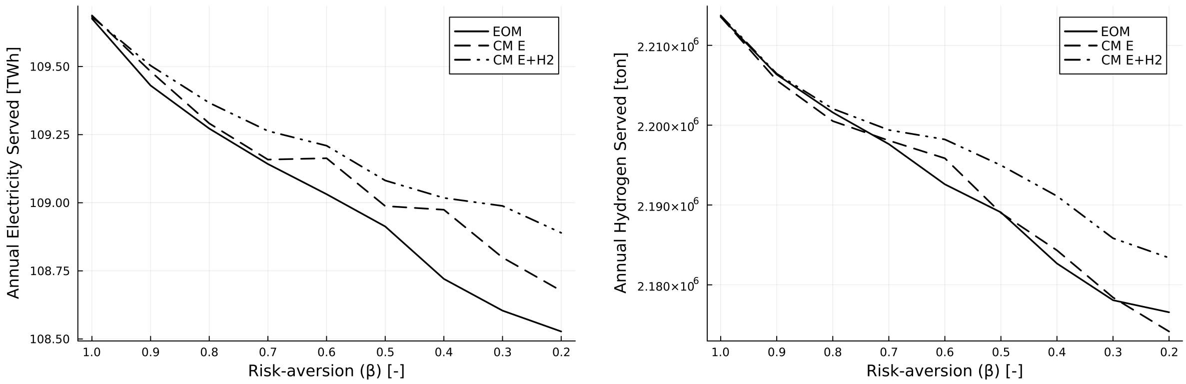
The addition of the hydrogen capacity market comes with interesting effects. Firstly, the hydrogen total installed capacity is restored with a capacity mix similar to the socially optimal one. However, electrolyzers' capacity is more sensitive to risk preferences, and storage capacity recovers, in general, more consistently when adding capacity markets. This is likely to be due to two factors. As seen in Figure 6.12(a), vRES capacity drops with risk aversion even when capacity markets are in place. This reduces electricity availability and comes with a coherent increase in the electricity price, making electrolyzers less attractive. In turn, storage can still benefit from price arbitrage, meaning that it can decide to buy cheap hydrogen during periods of vRES surpluses and eventually resell it at a competitive price. As it is assumed perfect foresight within a scenario, arbitrage opportunities might be similar even if expected profits are uncertain, reducing risk for the technology.

In general, the effectiveness of the hydrogen capacity market in restoring the original capacity mix is confirmed. At the same time, this comes with an interesting effect on the storage volume, as visualized in Figure 6.14(b). Storage volume is not remunerated in the hydrogen capacity market, and introducing risk aversion causes a drop of 1 TWh going from $\beta = 1.0$ to $\beta = 0.9$. However, the hydrogen capacity market makes the storage volume stabilize and no further reductions are observed, making the storage volume independent of risk. In other terms, after the initial drop, the storage volume is not affected by the risk as long as the discharge capacity is corrected.

6.3.2. Impact on System Adequacy

The average amount of energy served clarifies the correlation between the installed capacity and the resulting system adequacy. It measures the amount of demand served with respect to the exogenous demand. This indicator is preferred to the Energy Not Served as in a context of flexible demand, the latter is more difficult to define and does not necessarily lead to relevant results. Indeed, a price-elastic demand depends on the function definition, presenting at times no involuntary curtailment. It is therefore preferred to analyze the amount of energy served, as it explicitly presents how the cleared demand changes with the market conditions.

Figure 6.15 provides an aggregate perspective of the effect of risk aversion in reducing the served demand. This effect is mainly due to the price-elastic demand, which allows to adapt reduce or increase the demand when necessary. However, it is clear how, with respect to the optimal risk-neutral case, risk aversion reduces the served demand, as a consequence of less installed capacity. This is valid for both the electricity and the hydrogen sector. Focusing on the former (6.15(a)), risk aversion entails a reduction from 109.675 TWh of electricity served to 108.527 TWh per year. This reduction is effectively limited to 108.676 TWh when the electricity capacity market is introduced and to 108.889 TWh when also the hydrogen capacity market is introduced. On the other hand, the hydrogen sector (6.15(b)) experiences a reduction of up to 0.037 $Mton$ in the EOM case. The introduction of the electricity capacity market does not have a relevant effect in improving the amount of served hydrogen, while the hydrogen capacity market is able to dampen its reduction. It is important to note that, as expected, the served demand in the risk-neutral case represented by the blue curves coincides for the three market designs.



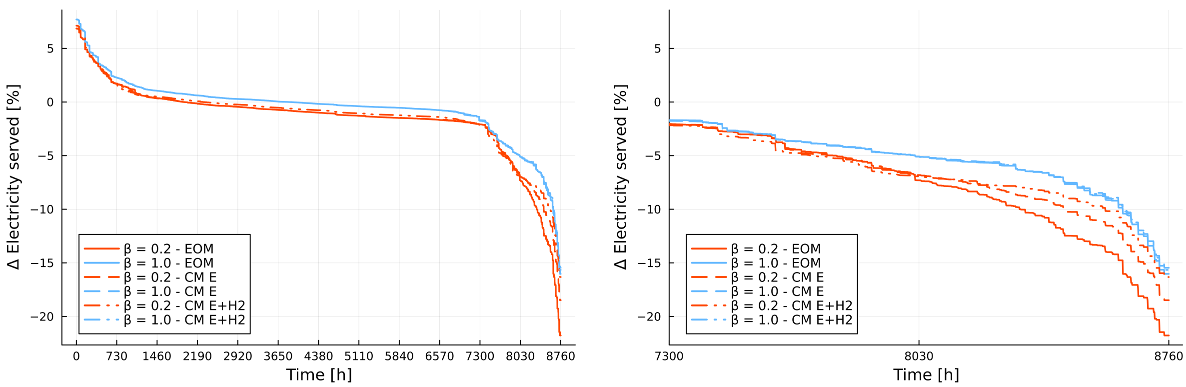
(a) Annual electricity served

(b) Annual hydrogen served

Figure 6.15: Annual energy served in (a) the electricity market and (b) the hydrogen market as a function of risk aversion in an EOM, EOM supported by a CM for electricity (CM E) and an EOM supported by a CM for electricity and a CM for hydrogen (CM E+H2)

Focusing on the extended year, Figure 6.16 presents the duration curve of the percentage of electricity served with respect to the historical electricity demand. The general reduction in the amount of electricity served when agents are risk-averse is confirmed, going from the blue line to the red line. While in the risk-neutral case the demand reduction can be handled by the price elasticity of the demand agent, a high degree of risk aversion ($\beta = 0.2$) implicates 42 hours of involuntary curtailment in EOM (the solid red line exceeds the reduction of 20% of the nominal demand, meaning curtailment is reached).

The introduction of capacity markets is beneficial. The centre of the figure below shows a slight improvement in the served electricity during baseload hours due to the dampening of vRES capacity reduction. However, their impact is more beneficial during scarcity periods. Ensuring an adequate amount of dispatchable capacity clearly improves demand reduction during those periods of extreme conditions when demand curtailment is more likely to happen. Again, looking at the far right side, curtailment is avoided on average, and in general extreme demand reduction due to price elasticity is limited. This effect is more pronounced when both the capacity markets, i.e. for electricity and hydrogen, are in place, as presented in the zoom of Figure 6.16(b). Indeed, the electricity capacity market can provide a higher capacity to supply the residual demand, while a hydrogen capacity market top-up it with available hydrogen for turbines.



(a) Duration curve - Full view

(b) Duration curve - Zoom on scarcity periods

Figure 6.16: Percentage of electricity served with respect to the historical demand in an EOM, EOM supported by a CM for electricity (CM E) and an EOM supported by a CM for electricity and a CM for hydrogen (CM E+H2)

Figure 6.17 presents the duration curve of the percentage of hydrogen served with respect to the nominal hydrogen demand. [3]

Focusing on the trend, it can be seen how the reduction due to risk aversion is more pronounced than in the electricity sector. This is again a manifestation of the risk exposition in two sectors: the reduction in hydrogen generation capacity is amplified by the reduction in the electricity generation capacity, which ultimately regulates hydrogen production.

The effect of introducing only an electricity capacity market does not improve the situation as it increases the demand for fuel from hydrogen turbines without ensuring a corresponding adequate increase in hydrogen generation capacity, as can be seen from the overlapping o the two curves. On the other hand, introducing the hydrogen capacity market ensures hydrogen availability and tends to bring the level of hydrogen served back to the risk-neutral case, even if its impact is limited. However, it is important to notice that the reduction of vRES capacity with respect to the risk-neutral case arises also here, as the lack of power generation limits the beneficial effect of capacity markets in ensuring the optimal levels of served hydrogen.

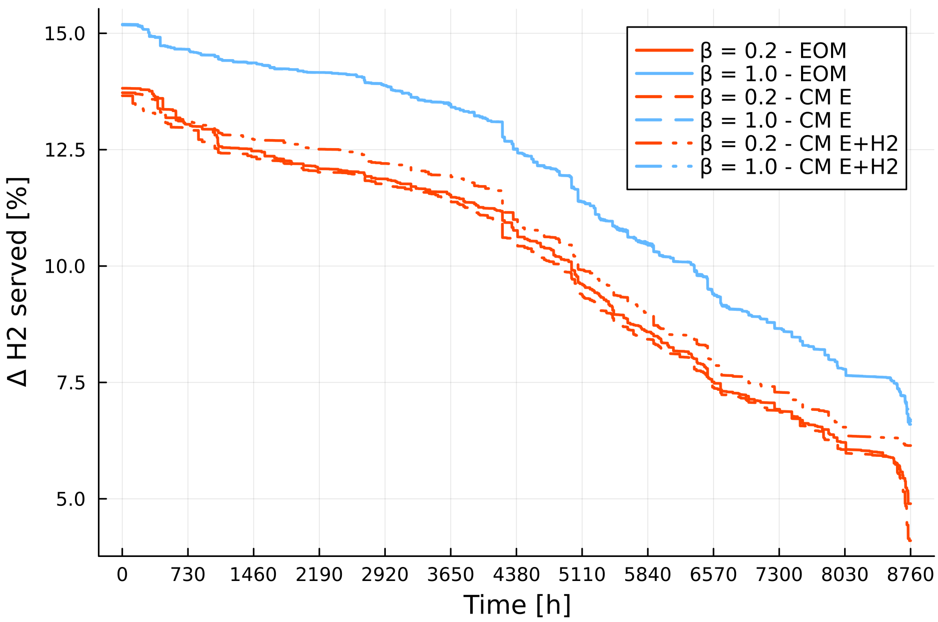


Figure 6.17: Percentage of hydrogen served with respect to the nominal demand in an EOM, EOM supported by a CM for electricity (CM E) and an EOM supported by a CM for electricity and a CM for hydrogen (CM E+H2)

Moving towards an analysis of market prices, Figure 6.18 presents the average electricity price duration curves for the three market designs, comparing the risk-neutral cases (in blue) to the case where agents are risk-averse for a degree of $\beta = 0.2$ (in red). Again, the blue curves, which represent prices under the risk-neutral case, coincide for the three market designs.

[3] It can be seen that hydrogen is served always in excess with respect to the nominal demand due to the parametrization. This is a consequence of the modelling of the hydrogen demand function based on the elasticity of the electricity demand, which does not necessarily refer to the magnitude of the hydrogen demand.

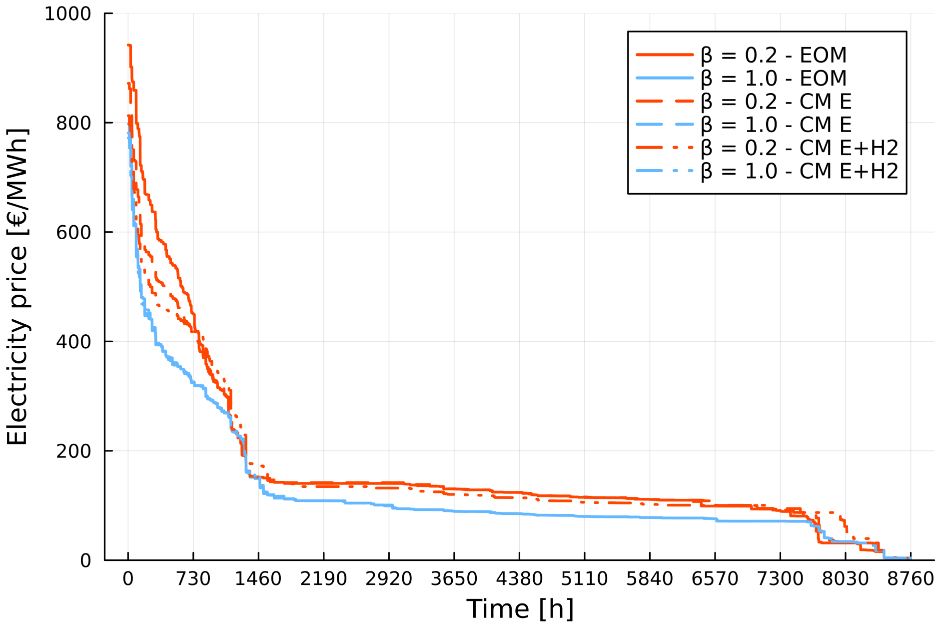


Figure 6.18: Comparison of electricity price duration curves for the three different market designs for risk-neutral agents and risk-averse agents

The average electricity price in the risk-neutral case is 122.89 €$/MWh$, while the median is 85.12 €$/MWh$. As introduced, the high share of vRES capacity drives prices downward, as can be seen from the flat section in the centre of the figure of sustained low prices. However, increasing risk aversion leads to higher prices as a result of a lower generation capacity combined with higher risk premiums. The average electricity price rises to 163.58 €$/MWh$ in an EOM with risk-averse agents, while the median increases to 123.89 €$/MWh$. In addition, periods of high prices are more, as investors require more periods with scarcity prices to recover their costs. This is evident when looking at the left side of the graph, where the curve for the risk-neutral case is more gentle and highlights lower prices.

The introduction of the electricity capacity market does not dampen the effect on low-demand price periods, as vRES capacity is not included and does not benefit from it. However, the increase in scarcity prices is partially dampened by the availability of dispatchable capacity. This market design allows reducing the average electricity price in the presence of risk-averse agents to 158.39 €$/MWh$, while the median remains 124.10 €$/MWh$.

On the other hand, a higher impact can be seen with the addition of the hydrogen capacity market. Indeed, it ensures to have cheaper and available hydrogen for dispatchable turbines, avoiding prices higher than 812 €$/MWh$ and reducing the number of hours of scarcity prices. Furthermore, it reduces the number of hours with price spikes. The indirect benefits seen for vRES capacity slightly lower also baseload electricity prices. The average electricity price reduces to 155.40 €$/MWh$ when risk-averse agents compete in the presence of also a hydrogen capacity market. At the same time, the recovered vRES capacity allows reducing the median electricity price to 114.52 €$/MWh$.

It must be noticed that, as can be seen on the right side of the figure below, the hydrogen capacity market ensures fewer periods of very low prices. Indeed, a higher hydrogen capacity that, in this case, is not compensated by a higher vRES capacity entails more periods of inframarginal profits for vRES generators.

Figure 6.19 presents the average hydrogen price duration curves for the three market designs, comparing the risk-neutral cases (in blue) to the case where agents are risk-averse for a degree of $\beta = 0.2$ (in red). As for the electricity price duration curve, also the hydrogen price duration curve is unvaried for the different market designs when agents are risk neutral, with an average hydrogen price of 4.14 €$/MWh$. As discussed in Section 6.1, the fluctuating trend is likely to be due to the combination of the impossibility to import and export and a limited price elasticity.

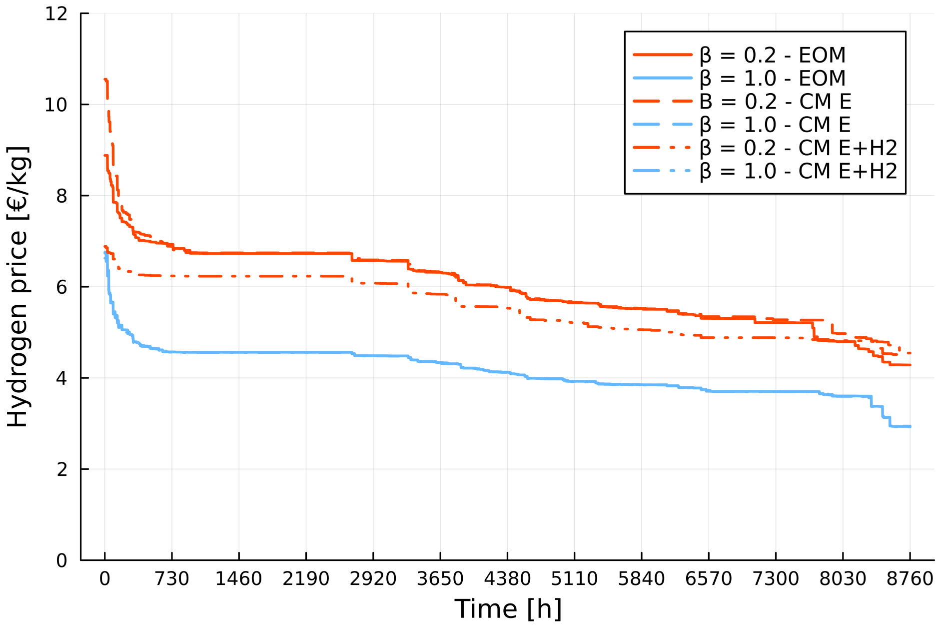


Figure 6.19: Comparison of hydrogen price duration curves for the three different market designs for risk-neutral agents and risk-averse agents

The increase in the degree of risk aversion leads to an important increase in hydrogen prices, making the average price rise up to 5.97 €$/kg$. Also here, the amplified effect due to risk exposition from both sectors is visible: higher electricity prices combined with the risk premium deriving from higher degrees of risk aversion affect hydrogen generation and in turn, make it less attractive. This implies a reduction in hydrogen installed capacity.

The introduction of an electricity capacity market in general does not enhance the hydrogen prices picture. The average hydrogen price is not practically affected, increasing to 6.04 €$/kg$, as the central region of the curve coincides for the two market designs. However, the average price gives limited information in this case, as the effect of this market design on the hydrogen price lies in scarcity hours and residual hours. On the left, it can be seen how average price spikes slightly increase in frequency, but in particular, in magnitude, reaching a maximum of more than 10 €$/kg$. This is attributable to the restoration of hydrogen turbine capacity, which introduces an increased hydrogen peak demand during periods of vRES scarcity. The fact that hydrogen turbine capacity is not however topped up by a discharge storage capacity in the hydrogen sector makes it competing with the hydrogen demand agents. At the same time, periods of low prices see the hydrogen price increase as well with respect to the EOM case.

The addition of the hydrogen capacity market evidently reduces the hydrogen prices, leading to an average price of 5.54 €$/kg$. This is not the only benefit, as ensuring an adequate capacity in the hydrogen supply reduces fluctuations and allows to have a stable electricity price. Hydrogen price is contained between 4.54 and 6.88 €$/kg$ in this market design, which however suffers an increase in the average price ultimately due to the vRES capacity reduction and the higher electricity prices with respect to the risk-neutral case that it leads.

6.3.3. Impact on Costs and Social Welfare of the System

The general consequence of risk aversion on the agents' strategies is represented by the reduction in investment in generation capacity. This entails consequences on social welfare and its distribution. Figure 6.20 presents the variation in social welfare with respect to the risk-neutral case for an increasing degree of risk aversion, distinguishing the effect on generators' profit (in green) and on consumers' welfare (in red). Social welfare is computed by accounting for the contribution of all the markets, therefore including both welfare from the EOMs and the capacity markets.

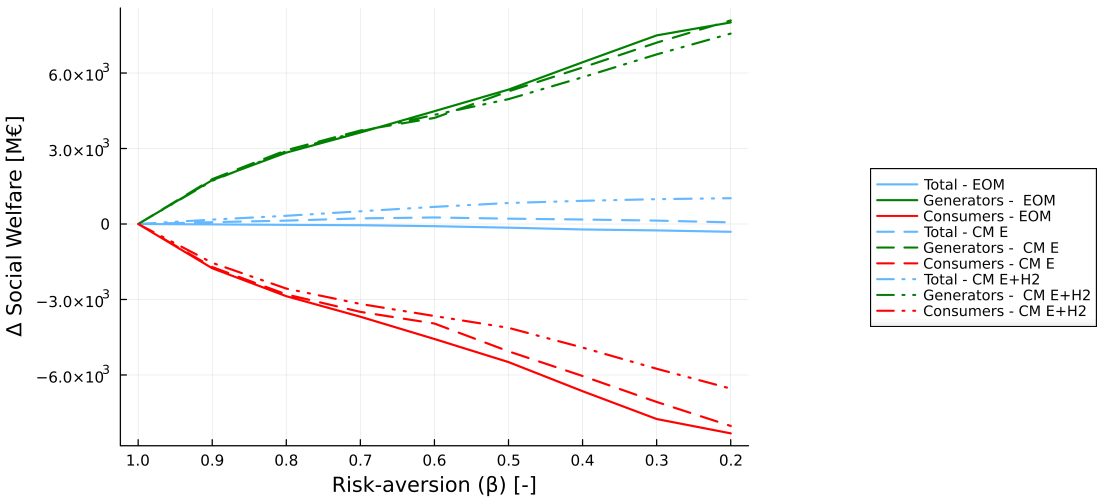


Figure 6.20: Variation in social welfare for the proposed three market designs with respect to the risk-neutral case as a function of the degree of risk aversion

As expected, the total social welfare decreases with risk aversion in the EOM. However, the introduction of capacity markets leads to an increase in it, which can likely be attributed to a combination of factors. As new markets are introduced, and so are the welfare associated with those markets, the comparison of social welfare becomes somewhat difficult. This effect of capacity markets, even though tested on a different model, can be found in the work of Petitet et al. (2017).

Comparing the effect of risk aversion on agents, it is evident how in an EOM this entails an important welfare transfer from consumers to generators, up to a total of 8025 million € per year. This effect is a result of the risk premium required by generators, which however leads to a general increase in the magnitude of prices and the frequency of periods of high prices (see Figure 6.18 and Figure 6.19). This results in long-term profit for generators at the expense of consumers.

Figure 6.21 present the cost of energy for consumers for the different market designs as a function of the degree of risk aversion. This indicator is computed as the total costs for consumers divided by the total energy supplied over all the scenarios.

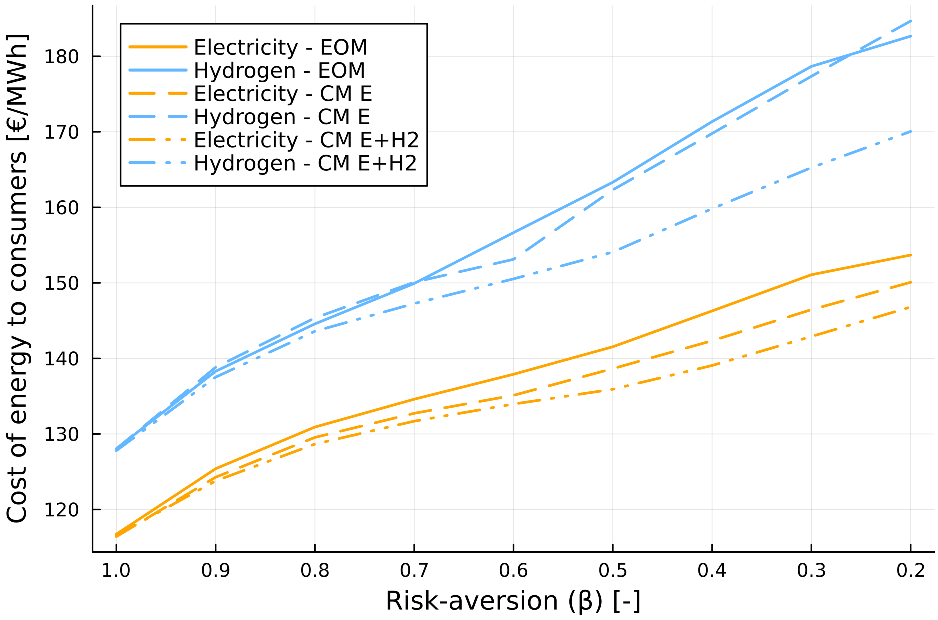
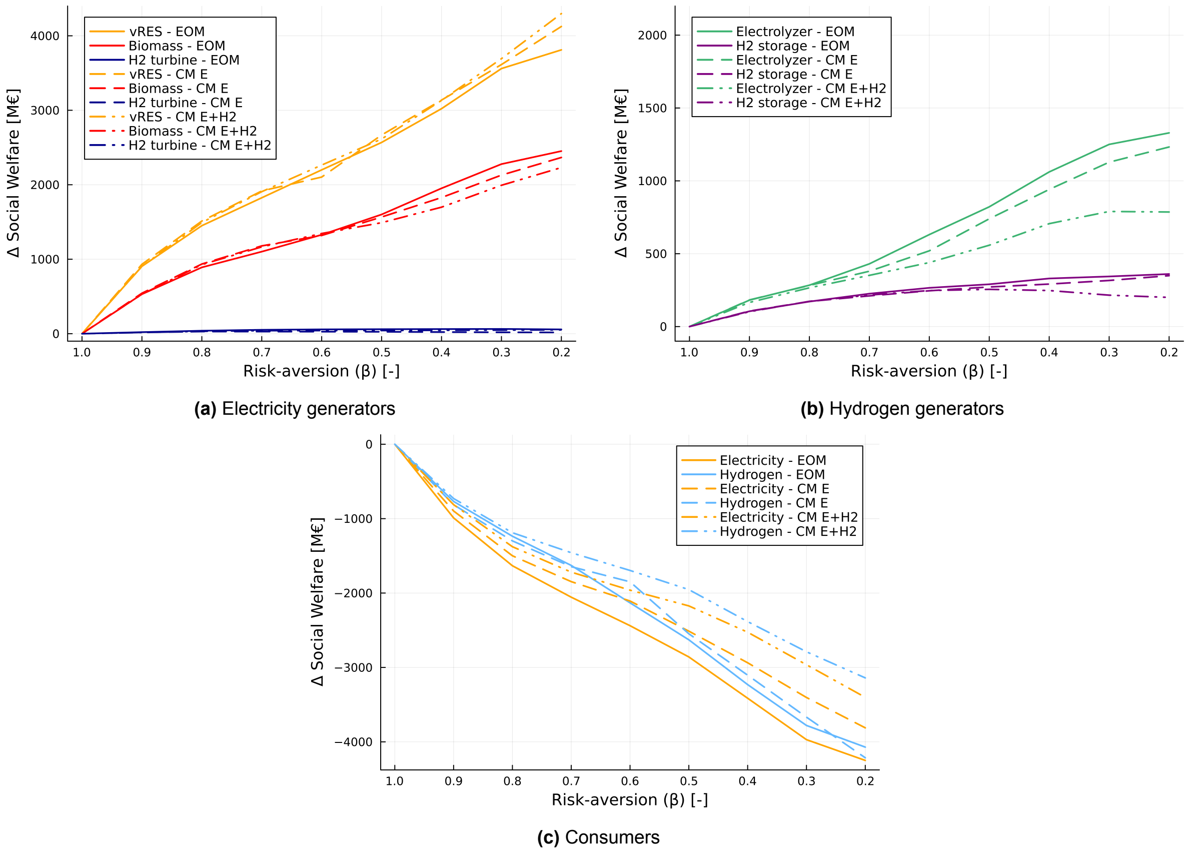


Figure 6.21: Cost of energy to consumers for the three different market designs as a function of the degree of risk aversion

As expected, risk aversion has a negative effect on consumers, which experience a higher cost of energy, and the introduction of capacity markets dampens this effect. Hydrogen consumers are more affected by risk aversion, as they suffer a higher increase in costs with respect to electricity consumers partly due to their exposition to risk from two markets. Furthermore, the ineffectiveness of the electricity capacity market on the hydrogen cost is clear, as the average cost for hydrogen consumers is not practically affected, while the introduction of the hydrogen capacity market constrains the cost increment. On the other hand, the reduction trend of the average cost of electricity to consumers is linear, as the introduction of capacity markets gradually limits the increase of the cost of electricity to consumers, which however is driven by the high vRES share in the capacity mix.

Figure 6.22 presents the variation of social welfare with risk aversion for the individual agents comprehending both generators and demand agents.



(a) Electricity generators

(b) Hydrogen generators

(c) Consumers

Figure 6.22: Variation in social welfare with respect to the risk-neutral case as a function of the degree of risk aversion - Singular agents

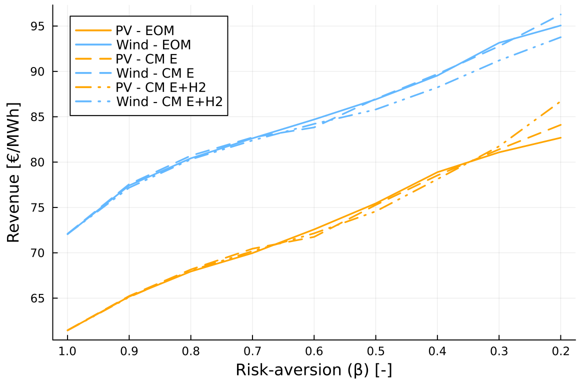
The welfare transfer trend is still recognizable, with an intensity proportional to the amount of installed capacity. It is however interesting to notice how biomass generators, which present an installed capacity well below the electrolyzers or storage discharge capacity, increase their profit more than the latter. This is in principle due to a high risk premium and a lower sensitivity o uncertainty. Indeed, it is important to remember how electrolysis and, indirectly, hydrogen storage, are demand agents in the electricity market, and the sub-optimal power generation capacity effects relapse on them as well. On the contrary, the electricity sector does not depend on hydrogen, apart from hydrogen turbines, which however account just for a very small share of the total installed capacity and supplied electricity (see Figure 6.2).

It is confirmed how the introduction of capacity markets in principle dampens the welfare transfer from consumers to generators. The electricity capacity market benefits electricity consumers, reducing their welfare loss; however, it is not effective on hydrogen consumers and is sometimes also negative. Instead, a clear beneficial effect for hydrogen consumers can be noticed when the hydrogen capacity market is added: the loss in welfare is limited to 3140 million € per year at the most, saving 1074 million € per year with respect to the worst case. At the same time, the hydrogen capacity market is also beneficial for electricity consumers.

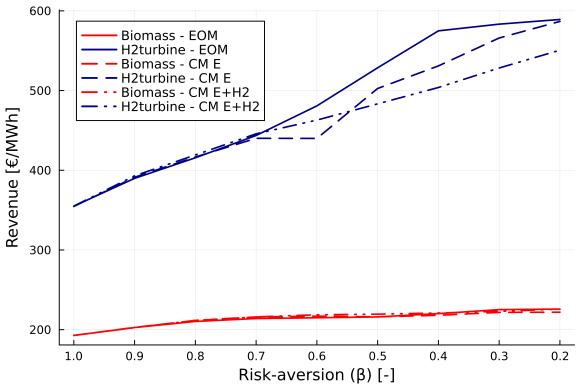
Looking at the effect on generators, all of them experience a reduction in long-term profit from the introduction of capacity markets, as a manifestation of how remunerating capacity reduces the risk premium they require. However, vRES generators show an opposite trend, increasing even more their profit. If it is true that they do not participate in capacity markets and they continue to be less keen to invest in the presence of risk, they are able to take advantage of the increased demand from the hydrogen sector for both storing hydrogen and ensuring the availability of the fuel for hydrogen turbines, confirming the insights of Hesel et al. (2022).

Diving more into the performances of particular agents, Figure 6.23 presents the required average revenue per MWh as a function of the degree of risk aversion. This is calculated as the total revenues of each technology divided by the total energy produced over all the scenarios.

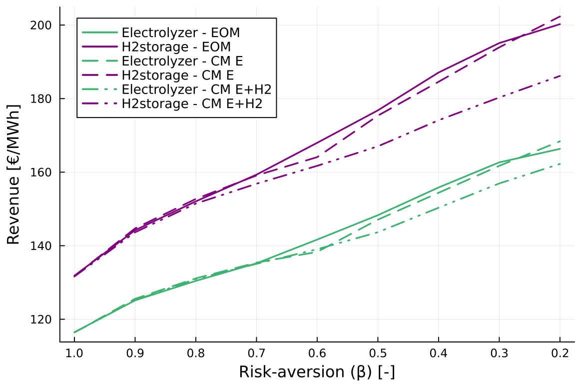
As expected, all the technologies increase their specific revenue with risk aversion as their reduction in installed capacity increases their deployment and corresponds to an increase in electricity prices.



(a) vRES generators



(b) Dispatchable electricity generators



(c) Hydrogen generators

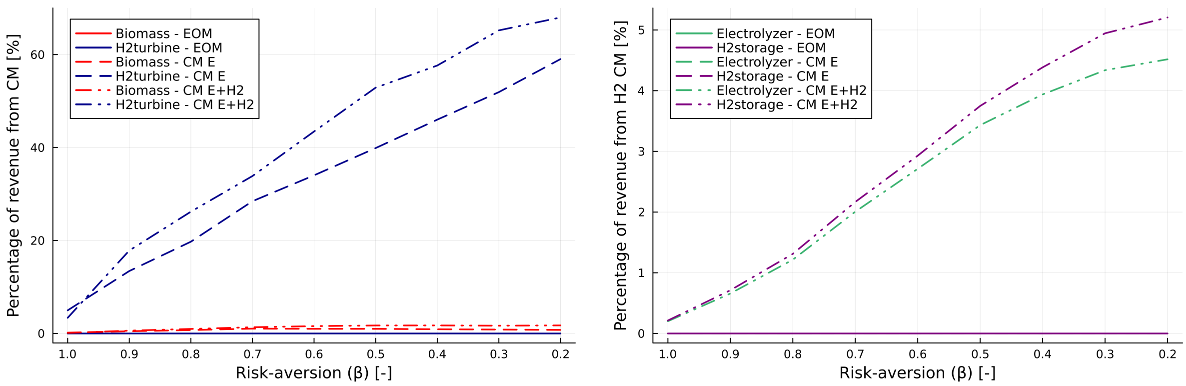
Figure 6.23: Average revenue per MWh of (a) dispatchable electricity generators, (b) vRES electricity generators and (c) hydrogen generators as a function of the degree of risk-aversion

It can be noticed how vRES technologies' revenues (Figure 6.23(b)) are the least affected by risk aversion and do not exceed 100 €$/MWh$, as they are the first generators activated to serve the demand. Similarly, biomass is more sensitive to risk aversion, but the introduction of capacity markets does not affect noticeably this trend. On the other hand, as can be seen in Figure 6.23(a) the specific revenues for hydrogen turbines are very sensitive to risk aversion and increase from 355 €$/MWh$ up to 589 €$/MWh$. When the electricity capacity market supports the increase in hydrogen turbine capacity without ensuring the firm availability of the hydrogen supply, the specific revenue is just partially affected, but the introduction of also the hydrogen capacity market limits the increase up to 551 €$/MWh$, confirming how capacity markets are able to reduce the need for extra profit from the EOM. The specific revenues for the hydrogen turbine could seem high, but this is in line with high LCOE of the technology of recent studies (e.g., (Hernandez & Gençer, 2021) and (ETN Young Engineers Committee, 2022)) and it is mainly justified by high costs of hydrogen combined with a small amount of supplied electricity.

Focusing on the hydrogen sector, Figure 6.23(c) presents the specific revenue per MWh of hydrogen (again, with respect to its LHV) as a function of the degree of risk aversion. Both electrolysis and storage are highly affected by risk aversion, as a consequence of their exposition to the effect of risk in the electricity sector. The electricity capacity market does not have a relevant effect on hydrogen supply agents' revenues while adding also a hydrogen capacity market is effective in dampening this effect for storage, which can take advantage of price arbitrage. On the other hand, total revenues for electrolysis are not very affected by the introduction of capacity markets.

The weight of revenues from capacity markets on total revenues is presented in Figure 6.24. The left subfigure highlights how hydrogen-fired turbines strongly rely on payments for capacity, as in high-risk aversion cases they earn up to more than 60% of their revenue from this market. This highlights how this technology is activated just in a very small amount of periods, and to ensure their participation a capacity market might be necessary. On the other hand, biomass' revenues are mainly from the electricity spot market, with capacity payments that account for less than 5% o the total revenues.

Considering the hydrogen capacity market, the subfigure on the right shows how the revenues from it account for up to 5% of the total revenues of electrolyzers and storage discharge, with a similar impact.



(a) Electricity capacity market **(b)** Hydrogen capacity market

Figure 6.24: Percentage of revenues from the capacity market as a function of the degree of risk aversion

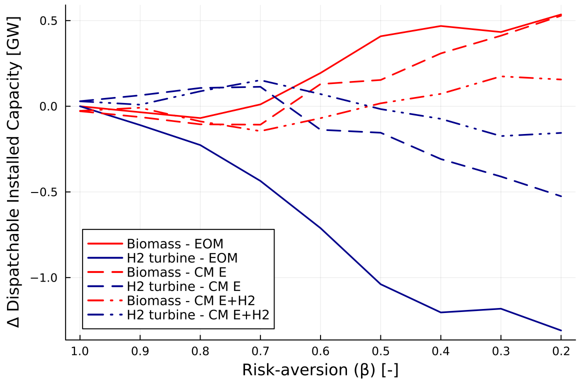
6.4. Fixing the Optimal vRES Capacity

This section presents the results of the model obtained from the simulations with a fixed vRES capacity, set at the risk-neutral socially optimal value. The purpose is to better understand the impact of vRES availability on the sector-coupling dynamics.

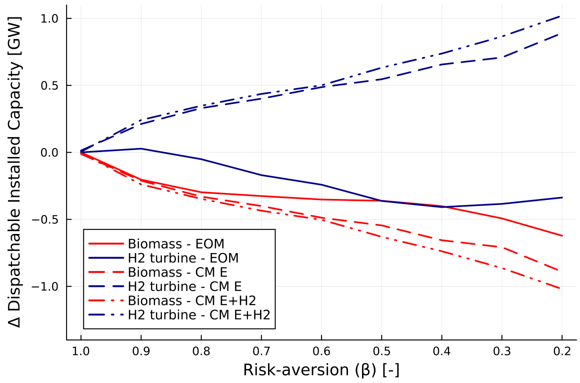
Figure 6.25 shows the impact of risk aversion on investment in dispatchable electricity capacity, comparing the trend of biomass generators and hydrogen-fired turbines. Figure 6.25(a) recalls the previous results obtained with an endogenously determined capacity. Figure 6.25(b) presents the results of the fixed vRES simulations and highlights how an increased vRES availability reduces the risk for hydrogen deployment. In the fixed vRES capacity case with an EOM, both biomass and hydrogen turbine generators present a similar decreasing trend. This is already opposed to the free vRES capacity case, in which the vRES reduction implies a hydrogen turbine capacity reduction of double the amount with respect to the fixed case, partially substituted by an increased biomass capacity.

The introduction of the electricity capacity market gives rise to the shift towards hydrogen turbines, which present low-capital costs, while worsening capacity reduction of capital-intensive biomass, reversing the tendency that arose from the vRES reduction. This phenomenon is strengthened by the addition of a hydrogen capacity market, which is able to ensure an enhanced hydrogen storage discharge capacity to fulfil turbines' demand.

Fixing vRES installed capacity, therefore, reverses the trend that risk aversion entails. More vRES capacity available corresponds to cheaper electricity, which benefits electrolyzers and hydrogen storage with a lower risk profile and, in turn, hydrogen turbines with cheaper hydrogen. This lower risk entails, in the presence of a market for capacity, a shift towards generators with lower-capital costs, which substitutes capital-intensive biomass capacity. This confirms previous findings on capacity markets effects highlighted in literature by, e.g., Kaminski et al. (2021) and Mays et al. (2019).



(a) Dispatchable capacity - Free vRES capacity case



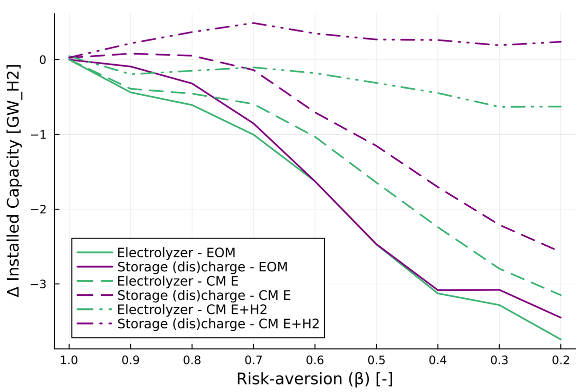
(b) Dispatchable capacity - Fixed vRES capacity case

Figure 6.25: Impact of risk aversion on dispatchable electricity installed capacity when (a) vRES capacity is endogenously determined and (b) vRES capacity is fixed as in the risk-neutral case

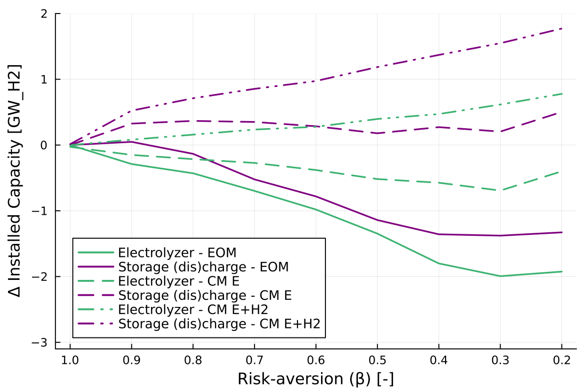
The effect of fixing vRES capacity is visible also on the hydrogen sector. Figure 6.26 presents the impact of risk aversion on electrolyzer and storage discharge capacity under the different market designs, comparing the case with free vRES capacity (Figure 6.26(a)) with the one with fixed vRES capacity (Figure 6.26(b)). Ensuring the optimal vRES capacity allows to halve the reduction of both technologies in case of an EOM. Also in the hydrogen sector, the opportunity to buy more cheap electricity benefits hydrogen production by decreasing their risk.

The introduction of a capacity market for electricity in this case not only dampens the reduction but is able to almost reestablish the optimal capacity.

The further introduction of the hydrogen capacity market leads to levels of investment higher than in the optimal risk-neutral case. This is a result of the reduced risk of hydrogen supply combined with the shift towards hydrogen turbine capacity, which entails a higher demand for storage discharge capacity.



(a) Hydrogen capacity - Free vRES capacity case

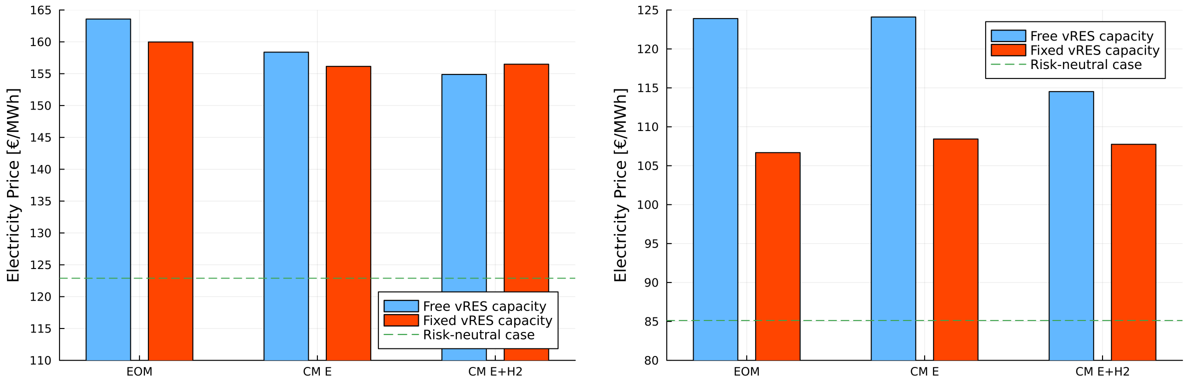


(b) Hydrogen capacity - Fixed vRES capacity case

Figure 6.26: Impact of risk aversion on hydrogen supply installed capacity when (a) vRES capacity is endogenously determined and (b) vRES capacity is fixed as in the risk-neutral case

The comparison of the trends of hydrogen capacity confirms how ensuring vRES availability plays a crucial role in decreasing the risk profile of hydrogen market agents. This can be noticed by comparing electricity prices and hydrogen prices for the free and fixed vRES capacity cases, which highlight a general decrease for the latter.

Figure 6.29(a) presents the average electricity prices for the three market designs comparing the free vRES case (in blue) and the fixed vRES case (in red) in the presence of risk-averse agents ($\beta = 0.2$). For the EOM and the electricity capacity market designs the average electricity price decreases by 3.6 €$/MWh$ and 2.2 €$/MWh$, respectively. On the other hand, the hydrogen and electricity capacity market design presents an increase in the average electricity price of 1.6 €$/MWh$. These trends do not highlight particular benefits in price decrease; however, recalling Figure 6.18, the high-prices region on the left might bias the analysis. Indeed, by considering the median of the hourly electricity prices in Figure 6.29(b), it is possible to see how prices in the central flat region of Figure 6.18 are pushed down by the increase in vRES capacity. These coincide with the periods of hydrogen generation and consequent storage, confirming how risk can be dampened by this reduction.



(a) Mean of the hourly electricity prices

(b) Median of the hourly electricity prices

Figure 6.27: Comparison of the (a) mean and (b) median of the hourly electricity prices for the risk-averse case of $\beta = 0.2$

The benefit of hydrogen generators is confirmed by the reduction of the average hourly hydrogen price. This is shown in Figure 6.28, comparing the three different market designs in the case of free and fixed vRES for a degree of risk aversion of $\beta = 0.2$. The effect of lower electricity prices in the flat region is transposed indeed on hydrogen prices. The average hydrogen price goes from 5.97 €$/kg$ to 5.24 €$/kg$ already in the EOM case. The reduction is however the same for the different market designs, as capacity markets basically affect peak production, while hydrogen prices are indeed driven by periods of vRES abundance.

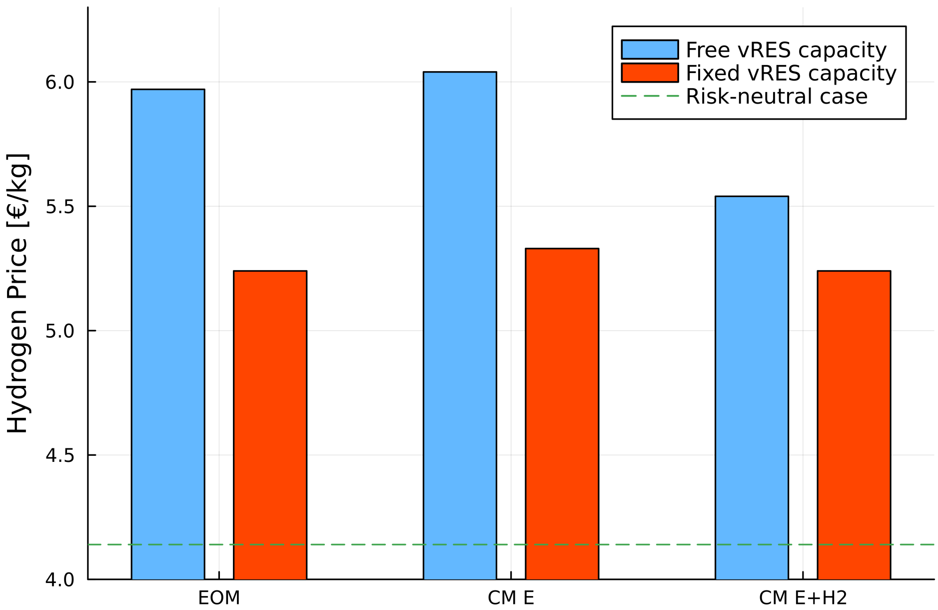
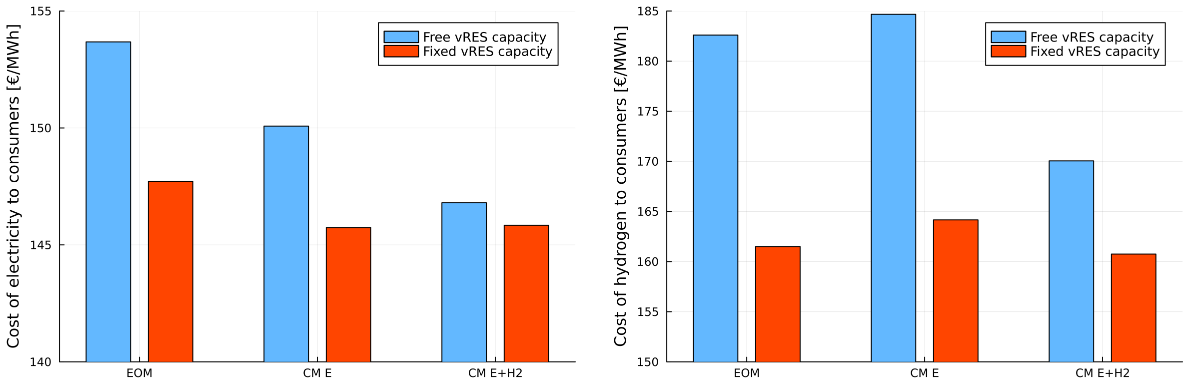


Figure 6.28: Comparison of the mean of the hourly hydrogen prices for the risk-averse case of $\beta = 0.2$

Reduced energy prices benefit consumers by reducing the cost of energy they have to face. Figure compares the different market designs for a degree of risk aversion of $\beta = 0.2$ in the case of free vRES capacity (in blue) and fixed vRES capacity (in red). It can be seen how the fixed vRES capacity case is more effective for hydrogen consumers.



(a) Cost of electricity to consumers

(b) Cost of hydrogen to consumers

Figure 6.29: Comparison of the (a) cost of electricity and (b) cost of hydrogen to consumers for the risk-averse case of $\beta = 0.2$

Finally, the previous effects obtained by having a fixed vRES capacity benefit the consumers by reducing their welfare transfer to generators. Taking Figure 6.20 as a benchmark, ensuring the optimal vRES capacity reduces the welfare transfer from consumers to generators in the case of a high degree of risk-aversion $\beta = 0.2$ of 25% for the EOM and the EOM supported by electricity capacity market designs, going respectively from 8010 to 6011 million € per year and from 8025 to 6055 million € per year. Adding the hydrogen capacity market limits the reduction of the welfare transfer by 10%, reducing it from 6542 to 5843 million € per year.

7 Discussion

Understanding the interactions within the integrated electricity and hydrogen system in function of the degree of risk aversion is crucial for shaping an adequate market design. This chapter proposes to contextualize the previously presented results to shed light on the necessary features of a decarbonized and integrated market.

Section 7.1 interprets the results and highlights the effects of risk combined with the tested market designs. Section 7.2 relates the results to the assumptions used.

7.1. Interpretation of Results

The system presents a capacity mix dominated by vRES, which accounts for 93% of the total electricity installed capacity, representing a potential long-term energy system as described by DNV (2022). This is in line with the end goal for the EU: a climate-neutral energy system integration with renewable hydrogen and renewable electricity at its core (European Commission, 2020).

A first important observation lies in the fact that, for the modelled system, marginal pricing allows vRES generators to recover their cost via the market even when vRES share is very high, in this case, 93% of the total installed electricity capacity. This is important when considering systems which largely rely on vRES, as their low operational costs might push down electricity prices and undermine cost recovery. This is confirmed for each market design.

As expected, in an EOM risk aversion entails a general reduction in investment in installed capacity for both sectors coupled with a general increase in electricity and hydrogen prices, as a result of the risk premium required by each technology.

From a social welfare perspective, this leads to a reduction of the social welfare derived from the wholesale energy market. The introduction of capacity markets, and the welfare of these markets, make the comparison more complex. However, it is evident how consumers experience a welfare decrease due to the increasing risk premium required by generators, which ultimately results in a welfare transfer from consumers to generators. This is clearly related to the increase in the cost of energy to consumers with risk aversion. This effect is amplified in the hydrogen sector due to its direct exposition to risk from multiple sources of uncertainty, making them more sensitive to the level of risk aversion.

Each technology adapts its strategy by considering how it can recover its costs, which in the presence of risk depends on the magnitude of the risk premium combined with the dependency of revenues on uncertain parameters.

vRES capacity exponentially decreases with the degree of risk aversion. This reduction is driven by the dual uncertainties associated with vRES availability and fluctuations in electricity demand, including the demand generated by electrolyzers. On the other hand, biomass capacity tends to substitute hydrogen turbine capacity. This shift is attributed to the stability of biomass availability and variable costs, which remain unaffected by uncertainty, and only depend on electricity prices. However, in the case of fixed vRES, this trend triggered by risk aversion is inverted: capital-intensive biomass reduces its installed capacity with risk aversion, and the addition of a capacity market entails a further shift towards hydrogen turbines. This confirms the importance of an adequate level of vRES capacity in ensuring competitive hydrogen prices to drive hydrogen turbine deployment.

As introduced, the high vRES share and its uncertain availability amplify the impact of uncertain electricity generation in shaping the risk characteristics of the different technologies. This not only impacts investments in electricity generation but also extends to investments in generating and storing hydrogen.

The impact of risk aversion on electricity prices leads to a general increase in the magnitude of both prices of the flat vRES-induced section and peak prices. Furthermore, the number of periods of high prices increase, as generators require more scarcity pricing to recover the risk premium. Since hydrogen production in this model relies entirely on electrolysis, the effect of risk aversion on the electricity sector plays a pivotal role, as the increase in electricity prices directly increases hydrogen prices. This is mainly driven by the vRES capacity reduction and increases the risk premium required by electrolyzers and hydrogen storage. The hydrogen price goes therefore from a reasonable value of 4.14 €$/kg$ (affected by high capital costs for vRES compared to the forecasted reduction by 2040) up to 6.04 €$/kg$, which makes green hydrogen out of the competition when compared to other hydrogen production methods. This entails a reduction in electrolyzer capacity followed by a reduction in storage discharge capacity and volume.

Another important feature of the hydrogen price duration curves is the fluctuating trend of the price. As discussed, this could be mainly due to the combination of limited price elasticity and vRES intermittency dependency with the impossibility to import and export in the system modelled. From this perspective, it can be therefore affirmed how it is important to diversify the hydrogen supply and allows trading as much as possible, as this could lower the price for green hydrogen and benefit investors with a more constant price, which would benefit risk profiles with less uncertainties. This is in line with the creation of a European Hydrogen backbone proposed by the EU (European Commission (2020); European Commission (2022)).

Hydrogen-fired turbines exhibited a strong reliance on the hydrogen price, which drives the deployment of the turbines and, consequently, investments in the backup capacity for the electricity sector when the agent is risk-averse. The fluctuating nature of hydrogen prices combined with an increase of up to 50% due to risk aversion leads to a reduction in hydrogen turbine capacity, as their deployment is limited.

Capacity markets proved their effectiveness in restoring the optimal mix and dampening the welfare reduction of consumers by ensuring lower prices and higher availability with respect to the EOM with risk-averse agents. From the perspective of generators, capacity markets effectively mitigate risk for participants in those markets. Nonetheless, while they lower the risk premium needed from these participants, capacity markets do not directly impact the risk premium associated with vRES. Therefore, vRES generators continue to require the risk premium and, as they represent the highest share of installed capacity, they drive the welfare increase for generators and limit the effect of capacity markets. This represents a first indicator of how it is fundamental to hedge risk for vRES to ensure better performance of the modelled system.

Derisking only dispatchable electricity generators by implementing an electricity capacity market proved to be not enough to restore the electrolyzers and storage capacity when vRES capacity is also reduced. In this case, beneficial effects for consumers are limited to the electricity sector. The average hydrogen price is not reduced, while scarcity prices increase without a congruent increase in the amount of hydrogen demand served.

Possible solutions that proved to be complementary to the electricity capacity market and stimulate investment in hydrogen capacity are two: remunerating electrolyzers and storage capacity with a hydrogen capacity market and ensuring an adequate vRES capacity.

7.1.1. The Effects of the Hydrogen Capacity Market

For the entire system to benefit and reduce the shift towards biomass, capacity markets must be implemented in both the electricity and hydrogen sectors. This proved to hedge risk for generators and to improve the performance of the market by reducing the cost of hydrogen to consumers and further reducing the cost of electricity to consumers, achieving a more beneficial comprehensive effect. More specifically, it is beneficial by mitigating periods of high prices.

In the electricity sector, consumers benefit from lower prices and a limited magnitude and duration of scarcity prices (Figure 6.18). However, this design demonstrated how its efficacy in reducing electricity prices in the flat region induced by vRES is limited. This region is indeed driven by vRES pricing and, even though the introduction of both capacity markets partially restores vRES capacity, the absence of a dedicated de-risking instrument prevents vRES capacity recovery.

However, vRES potential participation in the electricity capacity market, which would have to be derated according to their availability, would not necessarily be successful. As their contribution to peak demand is not known in principle, and the derating factor with it, the income from the capacity market could be little and have a weak effect on installed capacity. Therefore, a possible instrument that could help in hedging risk could be the introduction of Contracts for Difference (CFD), which would ensure a stable electricity price.

While the introduction of an electricity capacity market does not have any relevant effect on hydrogen prices, the hydrogen capacity market allows recovering the optimal electrolyzers and storage capacity and attracts back part of the vRES capacity.

From the hydrogen side, this design ensures both the backup capacity of hydrogen turbines and supplements this capacity with supply from the hydrogen sector, improving hydrogen availability. Indeed, the optimal hydrogen capacity mix is reestablished and results in lower energy prices (Figure 6.19) and higher served demand for both electricity and hydrogen compared to a risk-averse EOM (Figure 6.15). This has proven valid even considering that hydrogen turbines pay for ensuring firm capacity in the hydrogen capacity market, as their revenue for ensuring electricity capacity exceeds the cost of ensuring the corresponding hydrogen capacity.

Derisking electrolyzer and discharge capacity via the hydrogen capacity market also results in a dampened reduction of storage volume, which is not remunerated by the market. This is likely to be due to the higher potential charge and discharge, highlighting how for the modelled system the increase in electrolyzer capacity drives a partial increase in storage volume. Therefore, instruments that remunerate capacity can be considered beneficial also for the volume of hydrogen storage.

Even if the simulations did not highlight the necessity of remunerating storage availability, it is true that this could be needed considering potential extreme events (dunkelflaute) that must be covered by long-term hydrogen storage. This originates the need for an instrument such as a long-term energy contract for hydrogen availability during periods of scarcity that, stipulated by hydrogen turbines, allows hedging risk and ensures the backup to the electricity sector.

7.1.2. The Effects of Ensuring the Optimal vRES capacity

The critical step of hydrogen availability is closely linked to electricity prices originating from vRES generation. vRES pricing, indeed, is the driver of the hydrogen price. vRES availability is therefore ultimately crucial in stimulating hydrogen storage and improving its availability during periods of scarcity in the electricity sector.

By analyzing the effect of fixing the optimal risk-neutral vRES capacity on energy prices and, consequently, in installed capacity, it can be confirmed how de-risking vRES is fundamental for both sectors in reducing the effects of risk aversion. Ensuring the optimal risk-neutral vRES capacity reduces electricity prices, which benefits electrolyzers and, in turn, storage agents. This results in a decrease in the average hydrogen price (Figure 6.28). This ultimately makes hydrogen-fired turbines more profitable and attracts more investments in them. It can be affirmed that guaranteeing a backup capacity and avoiding involuntary curtailment requires an adequate vRES capacity, as it drives hydrogen availability at a reasonable price.

The reduction of green hydrogen production costs is important from the perspective of making green hydrogen compete with the other forms of hydrogen production and is currently at the centre of European policies. A clear example is the tool proposed by the H2Global Foundation (Bollerhey et al., 2022), a competition-based bidding procedure that ensures a long-term purchase agreement with the most favourable supplier could be a convenient instrument to achieve a cost reduction via market competition.

The correlation between hydrogen availability and the amount of vRES-electricity is further confirmed by the proportion of revenue that comes from the electricity capacity market for hydrogen turbines. In scenarios characterized by high risk aversion and vRES agents adapt their strategy by reducing investment, this revenue constitutes up to 60% of the total. However, when vRES capacity is fixed at the optimal level, this proportion drops to 35%, showing how the whole hydrogen sector benefits from a higher level of vRES.

This also indicates that the presence of ample vRES availability diminishes the necessity for capacity markets. In the context of optimal vRES capacity, the electricity capacity market is already enough to ensure the optimal amount of electrolyzer and discharge capacity. Furthermore, the hydrogen capacity market results in overinvestment in the hydrogen sector, as hydrogen turbines require more firm discharge capacity than in the risk-neutral case. Therefore, this case objects to the need for a hydrogen capacity market, as derisking vRES already benefits hydrogen generators with reduced uncertainty.

7.2. Limitations

The long-term equilibrium computed highlights how an integrated and decarbonized hydrogen and electricity system in the presence of risk-averse market participants is sensitive to risk aversion, which in an EOM in general entails underinvestment in generation capacity and worsens the performance in terms of system adequacy. By testing the integration of a capacity market for electricity and hydrogen, it is evident how these instruments are efficient in hedging risk and dampening the negative effects that the latter entails, reducing energy prices and costs for consumers by ensuring the optimal level of investment for those technologies participating in the capacity remuneration.

This section tries to clarify the effects of assumptions on the interpretation of the results.

The first important consideration lies in the technology data used. Using overnight costs for the technologies based on 2025 forecasts results in average hydrogen prices that range from 4.14 €$/kg$ for the risk-neutral case to 6.04 €$/kg$ for the highly risk-averse case. These values are higher than forecasted prices but are a result of the assumptions used for vRES overnight costs, which drive hydrogen production. This affects the utilization of hydrogen-fired turbines, increasing their dependency on revenues from the capacity market and reducing their deployment and investments, which could be higher in a system with cheaper vRES.

Another feature of the hydrogen price is its fluctuating behaviour (Figure 6.19). This is a result of the requirements of the model of clearing the market hourly combined with the impossibility of import and export. The latter assumption makes the system closed and therefore self-sufficient, requiring higher generation capacity with respect to the case with the possibility to trade energy with other nodes, which in general would result in a more efficient capacity mix.

A limitation of the model consists in considering a limited amount of technologies, which could oversimplify the picture of the decarbonized energy system. The first important missing technology concerns the electricity sector and consists of short-term electricity storage with batteries. Battery storage represents a flexibility measure that would increase the generation adequacy of the system by providing a high-efficiency solution to tackle vRES intermittency. It would represent a competitor of electrolyzers in the electricity market, but it would help to diversify the technology mix. Furthermore, the flexibility that short-term electricity storage would provide could affect the need for capacity markets, as system adequacy could be partially improved by reducing the magnitude and frequency of periods of high prices.

Considering the hydrogen sector, the model only considers electrolytic hydrogen. However, it is widely accepted that in the short and medium term, alternative low-carbon hydrogen sources are essential, such as Steam Methane Reforming equipped with Carbon, Capture and Storage (CCS). Green hydrogen will be still expensive in the short term and alternative sources are particularly crucial for lowering emissions from current hydrogen production methods and facilitating the concurrent adoption of renewable hydrogen solutions (European Commission, 2020). The inclusion in the model of SMR equipped with CCS could reduce the price of hydrogen and limit the sector-coupling effects of the integrated electricity and hydrogen system, improving the overall performance as it would avoid stress on the electricity system during moments of peak demand. This would of course also reduce the necessity of hydrogen storage, which however would not be beneficial from the perspective of security of supply.

Considering the demand side, the definition of a price-elastic demand introduces a source of flexibility that allows to correctly assess the need of capacity markets. As they represent a complementary instrument in ensuring generation adequacy, including flexibility sources allows to avoid the overestimation of the role of capacity markets. This however complicates the study of energy not-served, which is indeed avoided in this project, as involuntary curtailment could be reduced. Flexibility could hinder the true performance of a system, as this increased reliability may be counterbalanced by high consumer costs. It is therefore important to move from generation adequacy to system adequacy to truly analyze the performance of a system, and the degree of cost recovery and analysis of scarcity prices can be useful in clarifying the performances from a wider perspective (De Vries & Sanchez Jimenez, 2022).

The introduction of capacity markets in the market design is simplified, as the availability of generators is not always guaranteed by a firm capacity. In practice, no penalties or derating are accounted for those technologies which are not able to produce but are cleared in the capacity markets. For example, for the EOM with the inclusion of a capacity market for dispatchable electricity generators, hydrogen turbines would need to account for a penalty when they are activated but hydrogen is not available, as it could happen during a dunkelflaute. This would change their remuneration from the electricity capacity market, and their risk profile with it.

The introduction of the hydrogen capacity market allows hydrogen turbines to express a demand for capacity in the hydrogen capacity market to cover the capacity offered in the electricity capacity market. However, although this ensures an adequate storage discharge capacity, the hydrogen availability to cover eventual electricity shortages is not guaranteed.

Lastly, as discussed, vRES capacity is not remunerated by any mechanism or subsidy, and the effect of risk aversion is evident in the increase of electricity prices and the transfer of social welfare from consumers to generators. Underinvestment in vRES is not corrected by the increasing profitability guaranteed by the restored hydrogen capacity, as their risk profile is still dependent on uncertain availability. The sensitivity analysis conducted by fixing vRES capacity to the optimal risk-neutral result is useful in understanding their role and effect on the system but does not test any possible mechanism to derisk them.

8 Conclusion

The decarbonization of the electricity sector driven by the increase in vRES generation capacity comes with challenges due to an increasingly intermittent and unpredictable availability. According to the recent document *A hydrogen strategy for a climate-neutral Europe*, green hydrogen is expected to play a complementary role as, in addition to decarbonizing hard-to-abate sectors, it has the potential to provide the electricity system with long-term seasonal storage and increase the security of supply (European Commission, 2020). To effectively represent a sustainable contribution, hydrogen is expected to be produced by electrolysis powered by vRES electricity, ultimately depending on the electricity sector itself. Therefore, long-term storage would play a crucial role in ensuring the availability of green hydrogen during low vRES availability periods and increase system reliability (European Commission, 2020).

The resulting integrated electricity and hydrogen system is subject to new sector-coupling dynamics triggered by the interdependence of the two sectors, which makes the picture of managing and valuing assets more complex. The availability of the last hydrogen units has a high intrinsic value in a system highly dependent on uncertain vRES. In an EOM under perfect conditions, an adequate installed capacity is ensured by scarcity pricing remuneration. However, given the uncertainty of vRES availability and high investment costs, the presence of risk-averse investors might prevent reaching the adequate amount of installed capacity.

This thesis aims to analyze the impact of risk aversion on investments and its consequences in a decarbonized and integrated electricity and hydrogen system, evaluating the performances of EOMs and the possible beneficial effects of introducing an electricity capacity market for dispatchable generation and a hydrogen capacity market. To do so, it intends to answer the research question:

Which market design is best suited to trigger socially optimal investments in generation and storage capacity in a decarbonized and integrated electricity and hydrogen system with risk-averse agents?

To answer the proposed research question, a stylized stochastic equilibrium model has been developed to study the long-term equilibrium of a decarbonized integrated system resembling a potential Dutch scale. Risk aversion has been modelled using the CVAR metric and uncertainty is introduced with discrete scenarios which differ for electricity demand, vRES availability and hydrogen demand.

As proposed in the European hydrogen strategy (European Commission, 2020), a liquid market with commodity-based hydrogen trading would facilitate the entry of new producers and would be beneficial for deeper integration with other energy carriers. It would create viable price signals for investments and operational decisions. However, this thesis proved how risk aversion hinders the optimal amount of investment in both the electricity and hydrogen sectors, and instruments to hedge risk are necessary to create an efficient hydrogen market.

The introduction of risk aversion proved to reduce the levels of investment in both electricity and hydrogen capacity with respect to a risk-neutral situation. The impact on the hydrogen sector is amplified by its strong dependence on the electricity sector, which is similarly affected by risk. The reduction in electricity generation capacity as a result of higher risk premiums required and the consequent higher electricity prices affects the hydrogen sector with lower availability and higher operational costs for electrolyzers. These effects drive the reduction in electrolyzers and storage discharge capacity and are transposed on hydrogen turbine capacity, which ideally should ensure the security of supply of the system. The effect of risk aversion is ultimately transposed on consumers, which experience higher average prices for both energy vectors and more intense and frequent periods of high prices. They experience a higher cost of energy, which corresponds to a welfare transfer from consumers to generators in light of the risk premium required by the latter.

When vRES capacity is reduced due to investors' risk-averse behaviour, hydrogen turbine capacity is substituted by flexible capital-intensive biomass capacity, which is not affected by uncertainty in availability. Contrary to what is found in the literature, capital-intensive generation capacity is here preferred even in the presence of risk. This results from a different risk profile: even if they require a higher risk premium, capital-intensive assets in the model are better shielded from risk as they are less dependent on electricity and hydrogen prices and do not present any availability constraints. On the other hand, the exposition of hydrogen turbines exposition to risk can hinder a successful deployment even if they present low capital costs, as the large variation of external hydrogen demand and their strong dependence on electricity prices increase the uncertainty of the fuel supply and, therefore, worsens their risk profile.

The introduction of a capacity market for dispatchable electricity generators alone proved to not be enough in providing an adequate generation capacity for the integrated system, as its effects are limited to the electricity system. Hydrogen consumers experience the same reduction of served hydrogen and the same increase in the cost of hydrogen, experiencing even higher scarcity hydrogen prices. The strong dependence of hydrogen turbines on the supply chain requires a more comprehensive approach to ensure generation adequacy, confirming the need for additional measures to derisk the hydrogen sector.

The strategy of the EU for the creation of a European hydrogen backbone and the simultaneous supply from the global hydrogen market proposed in the REPowerEU document (European Commission, 2022) are aligned with reducing risk for hydrogen consumers (and hydrogen turbines as part of them), as they entail more competitive prices and reduce fluctuations by allowing cross-border trading in a wider area.

Furthermore, a direct instrument to derisk the hydrogen market is presented by the H2Global Foundation (Bollerhey et al., 2022), which proposed an innovative market-based mechanism to hedge risk from the uncertainty in hydrogen prices and demand and ramp up the hydrogen market. This consists of a combination of a long-term hydrogen purchase agreement for electrolyzers and a short-term hydrogen sales agreement with consumers, stipulated after a competition-based bidding procedure to ensure the most favourable prices. A funding body represents the contractual partner between the supply and the demand side and compensates differential costs.

Ensuring generation adequacy by the addition of a hydrogen capacity market highlights a positive impact in improving the performance of the system. The restored hydrogen capacity can take advantage of vRES surplus and reduce the average cost of hydrogen. At the same time, hydrogen turbines are more efficiently deployed and scarcity periods in the electricity sector are limited. As a result of the lower prices of both vectors, the welfare reduction of consumers is effectively dampened in both sectors. However, the market designs do not effectively limit the increase in generators' profit, as electricity prices are still influenced by the reduction of vRES capacity.

The lack of an instrument able to derisk vRES generators represents a shortcoming of the proposed designs, as the high share of vRES in the electricity mix drives hydrogen production. European initiatives, such as the REPowerEU plan and the European Hydrogen Bank (European Commission, 2023), recognise renewable capacity as a central requirement to generate electricity at low cost to make renewable hydrogen competitive with its fossil alternatives. This thesis proved that, if the effect of capacity markets on scarcity electricity prices is beneficial, vRES-driven prices are still increased, affecting the profitability of hydrogen assets. Furthermore, not derisking vRES limits the effect of the capacity markets in restoring the optimal distribution of welfare between consumers and generators.

Fixing the vRES capacity to the risk-neutral optimal level results in a decrease in electricity and consequently hydrogen prices, leading to an increase in the availability of hydrogen. This reduces the need for a hydrogen capacity market, as the optimal hydrogen capacity mix is already reestablished with the introduction of n electricity capacity market when adequate vRES capacity is ensured. This stresses the importance of the green hydrogen cost in an effective scale-up of the hydrogen infrastructure, which ultimately relies on vRES. It is, therefore, crucial to ensure the parallel increase of renewable electricity generation capacity by derisking investment in wind and solar technologies.

A first possible derisking measure for vRES generators is allowing the participation of derated vRES generators in the electricity capacity market. However, as vRES contribution to meet peak demand is not known in principle, and therefore their derating factors, the efficacy is not clear. A direct market-based support scheme might be more effective in derisking vRES. This could be obtained with the introduction of CfDs or PPAs for renewable generators, as proposed by the REPowerEU plan (European Commission, 2022). This would allow to ensure a stable and adequate electricity price.

To conclude, stakeholder feedback confirms the need for additional measures to reduce the very high costs associated with the risks that are not sufficiently addressed by EU financial instruments (European Commission, 2023). The introduction of capacity markets in both the hydrogen and electricity sector represents a possible viable and effective solution to hedge risk, but dedicated instruments to support vRES capacity such as CfDS are also needed, as such an integrated and interdependent system requires a comprehensive approach to ensure adequate investments in key technologies.

8.1. Policy Recommendations

The insights derived from the model provide policymakers with valuable considerations for shaping the electricity-hydrogen market.

As stressed, it is recommended to implement an electricity capacity market for dispatchable generators, as it allows to improve the performance of the electricity system during periods of vRES scarcity. However, this does not directly benefit the hydrogen sector, and further expedients to derisk electrolyzers and storage capacity are needed.

To directly derisk the supply side of the hydrogen sector, a hydrogen capacity market is recommended as, when combined with the electricity capacity market, it is able to ensure a hydrogen capacity mix and benefit both electricity and hydrogen consumers with a lower cost of energy. Furthermore, it improves to ensure an adequate capacity to top up hydrogen turbines. It is recommended to ensure this by allowing hydrogen turbines to express their demand for storage discharge capacity. Making hydrogen turbine generators pay for firm capacity could be beneficial in two different ways: by improving their reliability and by more equally allocating the cost of capacity required by hydrogen turbines, which would be paid by those who directly use it, instead of by hydrogen consumers.

However, even though the simulation does not advocate for it, dealing with the availability of hydrogen might be further considered: being unavailable during moments of scarcity should entail a penalty for turbines. To address this lack, it is recommended to consider an additional solution to improve the security of supply against extreme either events such as a dunkelflaute. This could consist of the stipulation of long-term energy contracts between hydrogen turbines and hydrogen storage to ensure the minimum availability of hydrogen for the backup.

An indirect solution to benefit the hydrogen sector is ensuring an adequate vRES capacity. vRES play a crucial role in a decarbonized system and derisking them proved to be fundamental in reducing hydrogen cost and uncertainty in the hydrogen market, boosting investment in electrolyzers and hydrogen storage. Furthermore, ensuring an adequate vRES capacity reduces the need for a hydrogen capacity market as electrolyzers already benefit from the increase of vRES-electricity availability, which makes them more profitable. Therefore, as their participation in the capacity market could be misleading, market-based instruments such as CfDs or PPAs would allow ensuring an adequate and stable electricity price, which would hedge risk for investment in vRES, and at the same time would benefit the hydrogen sector.

8.2. Recommendations for Future Research

It is important to understand how this work tried to bring to light possible sector-coupling dynamics of an integrated market for energy and capacity for electricity and hydrogen, which is a relatively new and unexplored topic. Therefore, there is room for improvement at multiple layers.

The first layer regards the assumptions. This work used historical data for the electricity demand. However, as the modelled energy system refers to a possible future scenario which could take place from 2040 onward, it could be interesting to use a forecasted long-term electricity demand. Furthermore, the introduction of additional technologies would be useful. In particular, the introduction of hydrogen generation from SMR equipped with CCS technology could be interesting. This would add a competitive hydrogen generator able, at least in the short-term, to reduce hydrogen prices and the need for hydrogen storage. However, it is not clear how a potential reduction of hydrogen storage would affect the system adequacy, in particular for the backup of the electricity system. On the other hand, short-term electrical storage could be added to investigate the effect of combining a flexibility source with a capacity market and, given the competition between short-term storage and electrolyzers, the potential effects on the energy sector.

In terms of market designs, it could be interesting to analyze how vRES could be remunerated out of the EOM to hedge risk. Possible alternatives are the participation of derated vRES generators in the electricity capacity market, but also the introduction of PPAs or CFDs.

The latter solution can be interesting also when considered in relation to electrolyzers availability. In the modelled system, there are no requirements imposed on the availability of hydrogen during peak demand periods, and electrolyzers' participation in the hydrogen capacity market without ensuring firm capacity is justified by their functioning during periods of vRES surplus. However, if the demand from hydrogen turbines is comparable to the hydrogen supply capacity, electrolysis must ensure a certain amount of hydrogen generation to fill up storage adequately. This could be indeed provided with Hydrogen Purchase Agreements or CfDs for electrolyzers.

Further research could also be conducted on the possibility to remunerate storage for its available energy in addition to its capacity, with the use of long-term energy contracts for availability. Indeed, if it has been verified how remunerating storage capacity indirectly benefits investments in storage volume, the impact of storage volume and its availability on system adequacy can be investigated further.

9 Personal Reflection

My experience during the MSc SET delighted me with a deep knowledge of the sustainable energy world and helped me understand where my passion positions within this world. Even if engineering is often associated with the creation of technology, I found most interesting the study of the interaction of different technologies. I understood how energy markets play a fundamental role in ensuring the best outcome for society in the energy world, and how a deep knowledge of them is crucial to design the optimal structure where technologies can flourish.

When I approached this master's thesis, I was thrilled by studying how integrated electricity and hydrogen markets with hydrogen long-term storage can be designed, as I really believe in the importance of this topic for the future of energy systems. Reflecting on the challenges of hydrogen from a market perspective and discussing with Kenneth and Laurens, I identified the impact of risk aversion on investment in such an integrated system as an important challenge, and this represented a perfect playground to test possible market corrections. Of course, when I started scoping, my ideas were more confused than now, as it was my first real approach to modelling energy markets. My initial goal was to test two different instruments to hedge risk: capacity markets for the hydrogen sector and contracts for differences for electrolyzers. Three weeks were enough to understand how studying integrated electricity and hydrogen markets could be a PhD topic.

After having written this thesis, I understood how a work of high quality does not necessarily investigates every shade of a topic, but most of the times provides a deep understanding of a particular feature of the bigger picture.

In the end, this thesis focused on the impact of risk aversion on investment in a decarbonized and integrated electricity and hydrogen system, testing the integration of capacity markets to EOM. The integration of long-term hydrogen storage, a not-so-studied but important feature for the future of energy systems, provides additional value.

Risk aversion represents the core of the project and the added value, as it sheds light on an important feature of real-world markets which is always present, and for the hydrogen market is particularly delicate. However, including risk aversion entails more complexity in terms of the modelling effort. The decision to develop and use a stochastic equilibrium model represented the most reasonable choice for the scope of the project, as it allows to include risk and see how specific agents react and adapt their strategy. Using an iterative technique such as ADMM, however, has been challenging. The power of this algorithm is undoubted, but its implementation, calibration and the (necessary) trial and error process to make every case converge have been intense. I have to admit that sometimes I felt under pressure and overpowered when the code was not working properly, but I am also proud of myself for having been able to master such a complex mathematical tool. Even if it has been challenging, moments of difficulty contributed to making me enjoy the feeling of getting results.

Studying the literature out there and applying it within the model allowed me to understand better the spot pricing theory and how this contributes to defining the energy mix. Furthermore, the inclusion of risk aversion enhanced my knowledge of market dynamics by making me understand what can be the impact of such market failure, considering the effects that investors have to face and how these are transposed to the performance of the energy system and, ultimately, to consumers.

As the flexibility of consumers is becoming an important instrument in improving market performance, demand agents have been modelled as price-elastic. This has been challenging in two situations. Firstly, for the calibration of the demand function for the hydrogen sector. Given the fact that there are no historical data for a market of green hydrogen, as this does not exist yet, finding a reasonable value required some trial-and-error attempts, and I recognized that sometimes I might have overthought it. Secondly, the flexible demand made more difficult the interpretation of the results, as it might hinder and dampen potential effects. However, as this represents an important feature of the systems of the future, I think this adds credibility to the work.

The development of the thesis proceeded with testing possible market designs and tools that can ensure adequate investment in generation capacity. This step represented a stimulating and challenging process that made me reflect on how the hydrogen assets should be remunerated to ensure the availability of hydrogen to back up the electricity system while providing green hydrogen at a competitive price. A first introduction of the electricity capacity market has been integrated to check the effect of ensuring backup for electricity without ensuring hydrogen turbine firm capacity. This confirmed the idea of a low deployment of hydrogen, as hydrogen turbines suffered from the uncertainty that affects the hydrogen sector when investors are risk-averse, entailing lower availability.

My focus has been on modelling the remuneration of storage discharge capacity to ensure an adequate backup during periods of scarcity alongside the remuneration of electrolyzers capacity to ensure the possibility to store an adequate amount of hydrogen during periods of vRES surplus. This combination has been conducted to check the potential supporting role of the two technologies, which complete themselves and work together rather than in competition. Furthermore, in order to ensure that the backup of the electricity system offered by hydrogen turbines was topped up by an adequate storage discharge capacity, hydrogen turbines have been modelled as a demand agent in the hydrogen capacity market.

A possible improvement that, due to time limitations, I had not the possibility to test is the remuneration of storage for ensuring its availability. The integration of long-term energy contracts for storage availability stipulated with hydrogen turbines would complete the picture of a design that could be beneficial in ensuring backup generation also during dunkelflaute, an essential feature in an energy system largely based on vRES.

At the end of the project, I am glad to have developed a deep understanding of the energy modelling world and the complex system it addresses, which is a combination of social, economic and technological perspectives. More generally, writing this thesis helped me to realize how much is important to reflect and the work of others, which is a starting point for building scientific knowledge, but also on your own work, as the final result is part of a process which is more than the sum of singular choices.

Studying the complexity and challenges of energy markets and trying to directly model them have been very constructive for me, and I am glad that my small contribution might help the scientific world in the energy transition.

References

Alvik, S., & Onur Özgün et al. (2022). *Hydrogen forecast to 2050* (Tech. Rep.). DNV. Retrieved from https://www.dnv.com/focus-areas/hydrogen/forecast-to-2050.html

Askeland, M., Jaehnert, S., & Korpås, M. (2019). Equilibrium assessment of storage technologies in a power market with capacity remuneration. *Sustainable Energy Technologies and Assessments*, *31*, 228-235. Retrieved from https://www.sciencedirect.com/science/article/pii/S221313881730601X doi: https://doi.org/10.1016/j.seta.2018.12.012

Ball, M., Wietschel, M., & Rentz, O. (2007). Integration of a hydrogen economy into the german energy system: an optimising modelling approach. *International Journal of Hydrogen Energy*, *32*(10), 1355-1368. Retrieved from https://www.sciencedirect.com/science/article/pii/S0360319906004927 doi: https://doi.org/10.1016/j.ijhydene.2006.10.016

Blanco, H., & Faaij, A. (2018). A review at the role of storage in energy systems with a focus on power to gas and long-term storage. *Renewable and Sustainable Energy Reviews*, *81*, 1049-1086. Retrieved from https://www.sciencedirect.com/science/article/pii/S1364032117311310 doi: https://doi.org/10.1016/j.rser.2017.07.062

Bollerhey, T., Exenberger, M., Geyer, F., & Westphal, K. (2022). Policy Brief 01/2022 - H2Global - Idea, Instrument and Intentions. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421522001161

Brito-Pereira, P., Mastropietro, P., Rodilla, P., Barroso, L. A., & Batlle, C. (2022). Adjusting the aim of capacity mechanisms: Future-proof reliability metrics and firm supply calculations. *Energy Policy*, *164*, 112891. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421522001161 doi: https://doi.org/10.1016/j.enpol.2022.112891

Bruninx, K., Moncada, J. A., & Ovaere, M. (2022). Electrolytic hydrogen has to show its true colors. *Joule*, *6*(11), 2437-2440. Retrieved from https://www.sciencedirect.com/science/article/pii/S2542435122004731 doi: https://doi.org/10.1016/j.joule.2022.09.007

Bruninx, K., Ovaere, M., & Delarue, E. (2020). The long-term impact of the market stability reserve on the EU emission trading system. *Energy Economics*, *89*, 104746. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140988320300852 doi: https://doi.org/10.1016/j.eneco.2020.104746

Bublitz, A., Keles, D., Zimmermann, F., Fraunholz, C., & Fichtner, W. (2019). A survey on electricity market design: Insights from theory and real-world implementations of capacity remuneration mechanisms. *Energy Economics*, *80*, 1059-1078. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140988319300453 doi: https://doi.org/10.1016/j.eneco.2019.01.030

Dagoumas, A. S., & Koltsaklis, N. E. (2019). Review of models for integrating renewable energy in the generation expansion planning. *Applied Energy*, *242*, 1573-1587. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261919306117 doi: https://doi.org/10.1016/j.apenergy.2019.03.194

De Maere d'Aertrycke, G., Ehrenmann, A., & Smeers, Y. (2017). Investment with incomplete markets for risk: The need for long-term contracts. *Energy Policy*, *105*, 571-583. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421517300411 doi: https://doi.org/10.1016/j.enpol.2017.01.029

De Vries, L. (2004). *Securing the public interest in electricity generation markets, the myths of the invisible hand and the copper plate* (Doctoral dissertation). Delft University of Technology.

De Vries, L. (2007). Generation adequacy: Helping the market do its job. *Utilities Policy*, *15*(1), 20-35. Retrieved from https://www.sciencedirect.com/science/article/pii/S0957178706000488 doi: https://doi.org/10.1016/j.jup.2006.08.001

De Vries, L., & Sanchez Jimenez, I. (2022, 02). Market signals as adequacy indicators for future flexible power systems. *Oxford Open Energy*, *1*. Retrieved from https://academic.oup.com/ooenergy/article/doi/10.1093/ooenergy/oiab007/6529239 doi: https://doi.org/10.1093/ooenergy/oiab007

DNV. (2022). *Energy transition outlook 2022* (Tech. Rep.). Author. Retrieved from https://www.dnv.com/energy-transition-outlook/download.html

Ehrenmann, A., & Smeers, Y. (2011). Generation capacity expansion in a risky environment: A stochastic equilibrium analysis. *Operations Research*, *59*(6), 1332–1346. Retrieved from https://pubsonline.informs.org/doi/epdf/10.1287/opre.1110.0992 doi: https://doi.org/10.1287/opre.1110.0992

Elberry, A. M., Thakur, J., & Veysey, J. (2021). Seasonal hydrogen storage for sustainable renewable energy integration in the electricity sector: A case study of finland. *Journal of Energy Storage*, *44*, 103474. Retrieved from https://www.sciencedirect.com/science/article/pii/S2352152X21011580 doi: https://doi.org/10.1016/j.est.2021.103474

ETN Young Engineers Committee. (2022). *Hydrogen deployment in centralised power generation - a techno-economic case study* (Tech. Rep.). European Turbine Network (ETN). Retrieved from https://etn.global/wp-content/uploads/2022/06/H2-deployment-in-centralised-power-generation-techno-economic-study-April2022.pdf

European Commission. (2020). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions - A hydrogen strategy for a climate-neutral Europe* (Tech. Rep.).

European Commission. (2022). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions – REPowerEU Plan* (Tech. Rep.).

European Commission. (2023). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions – on the European Hydrogen Bank* (Tech. Rep.).

Fraunholz, C., Keles, D., & Fichtner, W. (2021). On the role of electricity storage in capacity remuneration mechanisms. *Energy Policy*, *149*, 112014. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421520307254 doi: https://doi.org/10.1016/j.enpol.2020.112014

Gonzato, S., Bruninx, K., & Delarue, E. (2021). Long term storage in generation expansion planning models with a reduced temporal scope. *Applied Energy*, *298*, 117168. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261921006000 doi: https://doi.org/10.1016/j.apenergy.2021.117168

Green, R., Hu, H., & Vasilakos, N. (2011). Turning the wind into hydrogen: The long-run impact on electricity prices and generating capacity. *Energy Policy*, *39*(7), 3992-3998. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421510008311 doi: https://doi.org/10.1016/j.enpol.2010.11.007

Groenenberg, R., Juez-Larré, J., Goncalves, C., Wasch, L., Dijkstra, H., Wassing, B., … Kranenburg-Bruinsma, K. (2020). *Large-scale energy storage in salt caverns and depleted gas fields* (Tech. Rep.). TNO. Retrieved from https://repository.tno.nl//islandora/object/uuid:668d330c-1abe-4fc3-b191-d2741a2e6a78

Haas, J., Cebulla, F., Nowak, W., Rahmann, C., & Palma-Behnke, R. (2018). A multi-service approach for planning the optimal mix of energy storage technologies in a fully-renewable power supply. *Energy Conversion and Management*, *178*, 355-368. Retrieved from https://www.sciencedirect.com/science/article/pii/S0196890418310987 doi: https://doi.org/10.1016/j.enconman.2018.09.087

Hernandez, D. D., & Gençer, E. (2021). Techno-economic analysis of balancing california's power system on a seasonal basis: Hydrogen vs. lithium-ion batteries. *Applied Energy*, *300*, 117314. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261921007261 doi: https://doi.org/10.1016/j.apenergy.2021.117314

Hesel, P., Braun, S., Zimmermann, F., & Fichtner, W. (2022). Integrated modelling of european electricity and hydrogen markets. *Applied Energy*, *328*, 120162. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261922014192 doi: https://doi.org/10.1016/j.apenergy.2022.120162

Hörsch, J., Brown, T., Hofmann, F., Neumann, F., Frysztacki, M., Hampp, J., & Schlachtberger, D. (2023). *PyPSA-Eur: An open optimisation model of the European transmission system.* Zenodo. Retrieved from https://doi.org/10.5281/zenodo.7646758 doi: 10.5281/zenodo.7646758

Höschle, H. (2018). *Capacity mechanisms in future electricity markets* (Doctoral dissertation). Katholieke Universiteit Leuven.

Höschle, H., Le Cadre, H., Smeers, Y., Papavasiliou, A., & Belmans, R. (2018). An admm-based method for computing risk-averse equilibrium in capacity markets. *IEEE Transactions on Power Systems*, *33*(5), 4819-4830. doi: 10.1109/TPWRS.2018.2807738

IEA. (2019). *The future of hydrogen* (Tech. Rep.).

IEA. (2020). *The Netherlands 2020 - Energy Policy Review* (Tech. Rep.).

IEA. (2022). *World Energy Outlook 2022* (Tech. Rep.).

Joskow, P. L. (2008). Capacity payments in imperfect electricity markets: Need and design. *Utilities Policy*, *16*(3), 159-170. Retrieved from https://www.sciencedirect.com/science/article/pii/S0957178707000926 doi: https://doi.org/10.1016/j.jup.2007.10.003

Kaminski, S. (2022). *On the need, impact, and design of capacity remuneration mechanisms* (Doctoral dissertation). Katholieke Universiteit Leuven.

Kaminski, S., Höschle, H., & Delarue, E. (2021). Impact of capacity mechanisms and demand elasticity on generation adequacy with risk-averse generation companies. *Electric Power Systems Research*, *199*, 107369. Retrieved from https://www.sciencedirect.com/science/article/pii/S0378779621003503 doi: https://doi.org/10.1016/j.epsr.2021.107369

Keppler, J. H., Quemin, S., & Saguan, M. (2022). Why the sustainable provision of low-carbon electricity needs hybrid markets. *Energy Policy*, *171*, 113273. Retrieved from https://www.sciencedirect.com/science/article/pii/S030142152200492X doi: https://doi.org/10.1016/j.enpol.2022.113273

Koirala, B., Hers, S., Morales-España, G., Özge Özdemir, Sijm, J., & Weeda, M. (2021). Integrated electricity, hydrogen and methane system modelling framework: Application to the dutch infrastructure outlook 2050. *Applied Energy*, *289*, 116713. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261921002336 doi: https://doi.org/10.1016/j.apenergy.2021.116713

Kotzur, L., Markewitz, P., Robinius, M., & Stolten, D. (2018). Time series aggregation for energy system design: Modeling seasonal storage. *Applied Energy*, *213*, 123-135. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261918300242 doi: https://doi.org/10.1016/j.apenergy.2018.01.023

Kozlova, M., & Overland, I. (2022). Combining capacity mechanisms and renewable energy support: A review of the international experience. *Renewable and Sustainable Energy Reviews*, *155*, 111878. Retrieved from https://www.sciencedirect.com/science/article/pii/S136403212101145X doi: https://doi.org/10.1016/j.rser.2021.111878

Li, X., & Mulder, M. (2021). Value of power-to-gas as a flexibility option in integrated electricity and hydrogen markets. *Applied Energy*, *304*, 117863. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261921011855 doi: https://doi.org/10.1016/j.apenergy.2021.117863

Lux, B., & Pfluger, B. (2020). A supply curve of electricity-based hydrogen in a decarbonized european energy system in 2050. *Applied Energy*, *269*, 115011. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261920305237 doi: https://doi.org/10.1016/j.apenergy.2020.115011

Lynch, M., Devine, M. T., & Bertsch, V. (2018). *The role of power-to-gas in the future energy system: How much is needed and who wants to invest?* (ESRI Working Paper No. 590). Retrieved from http://hdl.handle.net/10419/193927

Mays, J., Morton, D. P., & O'Neill, R. P. (2019). Asymmetric risk and fuel neutrality in electricity capacity markets. *Nature Energy*, *4*, 948-956. Retrieved from https://www.nature.com/articles/s41560-019-0476-1 doi: https://doi.org/10.1038/s41560-019-0476-1

Michalski, J., Bünger, U., Crotogino, F., Donadei, S., Schneider, G.-S., Pregger, T., … Heide, D. (2017). Hydrogen generation by electrolysis and storage in salt caverns: Potentials, economics and systems aspects with regard to the german energy transition. *International Journal of Hydrogen Energy*, *42*(19), 13427-13443. Retrieved from https://www.sciencedirect.com/science/article/pii/S0360319917306109 doi: https://doi.org/10.1016/j.ijhydene.2017.02.102

Neuhoff, K., & De Vries, L. (2004). Insufficient incentives for investment in electricity generations. *Utilities Policy*, *12*(4), 253-267. Retrieved from https://www.sciencedirect.com/science/article/pii/S0957178704000682 doi: https://doi.org/10.1016/j.jup.2004.06.002

Newbery, D., Pollitt, M. G., Ritz, R. A., & Strielkowski, W. (2018). Market design for a high-renewables european electricity system. *Renewable and Sustainable Energy Reviews*, *91*, 695-707. Retrieved from https://www.sciencedirect.com/science/article/pii/S1364032118302454 doi: https://doi.org/10.1016/j.rser.2018.04.025

Ousman Abani, A., Hary, N., Rious, V., & Saguan, M. (2018). The impact of investors' risk aversion on the performances of capacity remuneration mechanisms. *Energy Policy*, *112*, 84-97. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421517306316 doi: https://doi.org/10.1016/j.enpol.2017.10.008

Petitet, M., Finon, D., & Janssen, T. (2017). Capacity adequacy in power markets facing energy transition: A comparison of scarcity pricing and capacity mechanism. *Energy Policy*, *103*, 30-46. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421516306966 doi: https://doi.org/10.1016/j.enpol.2016.12.032

Pfenninger, S., Hawkes, A., & Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, *33*, 74-86. Retrieved from https://www.sciencedirect.com/science/article/pii/S1364032114000872 doi: https://doi.org/10.1016/j.rser.2014.02.003

Roach, M., & Meeus, L. (2020). The welfare and price effects of sector coupling with power-to-gas. *Energy Economics*, *86*, 104708. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140988320300475 doi: https://doi.org/10.1016/j.eneco.2020.104708

Rockafellar, R., & Uryasev, S. (2000). Optimization of conditional value-at-risk. *The Journal of Risk*, *2*(3), 21-41. doi: https://doi.org/10.21314/jor.2000.038

Schmitz, K., Steffen, B., & Weber, C. (2013). *Incentive or impediment? The impact of capacity mechanisms on storage plants* (RSCAS Working Papers No. 46). Retrieved from http://hdl.handle.net/1814/27414

Scott, I. J., Carvalho, P. M., Botterud, A., & Silva, C. A. (2021). Long-term uncertainties in generation expansion planning: Implications for electricity market modelling and policy. *Energy*, *227*, 120371. Retrieved from https://www.sciencedirect.com/science/article/pii/S0360544221006204 doi: https://doi.org/10.1016/j.energy.2021.120371

Staffell, I., Scamman, D., Velazquez Abad, A., Balcombe, P., Dodds, P. E., Ekins, P., … Ward, K. R. (2019). The role of hydrogen and fuel cells in the global energy system. *Energy Environmental Science*, *12*, 463-491. Retrieved from https://pubs.rsc.org/en/content/articlelanding/2019/EE/C8EE01157E doi: http://dx.doi.org/10.1039/C8EE01157E

van Leeuwen, C., & Mulder, M. (2018). Power-to-gas in electricity markets dominated by renewables. *Applied Energy*, *232*, 258-272. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261918315319 doi: https://doi.org/10.1016/j.apenergy.2018.09.217

Vandewalle, J., Bruninx, K., & D'haeseleer, W. (2015). Effects of large-scale power to gas conversion on the power, gas and carbon sectors and their interactions. *Energy Conversion and Management*, *94*, 28-39. Retrieved from https://www.sciencedirect.com/science/article/pii/S0196890415000424 doi: https://doi.org/10.1016/j.enconman.2015.01.038

Vanegas Cantarero, M. M. (2020). Of renewable energy, energy democracy, and sustainable development: A roadmap to accelerate the energy transition in developing countries. *Energy Research Social Science*, *70*, 101716. Retrieved from https://www.sciencedirect.com/science/article/pii/S2214629620302917 doi: https://doi.org/10.1016/j.erss.2020.101716

A

Equilibrium Problem (Validation Step)

This section of the Appendix presents the deterministic equilibrium problem and the formulation of the respective KKT conditions, which are used as a comparison to the equivalent optimization problem presented in Appendix B during the validation of the model.

A.1. RES generators optimization problem

Decision variables: $\chi_r = (e_{r,dt}, cap_r)$

$$\max_{\chi_r \in X_r} \quad \Pi_r(\chi_r, \lambda^e_{dt}) = \sum_d W_d \sum_t (\lambda^e_{dt} - VC_r) e_{r,dt} - cap_r IC_r \tag{A.1}$$

subject to

$$0 \leq e_{r,dt} \leq cap_r A_{r,dt} \qquad (\underline{\delta}^e_{r,dt}, \overline{\delta}^e_{r,dt}) \qquad \forall d,t \tag{A.2}$$

$$0 \leq y_r \qquad (\overline{\delta}^c_r) \tag{A.3}$$

Rewriting this optimization problem with the KKT conditions:

$$-W_d(\lambda^e_{dt} - VC_r) - \underline{\delta}^e_{r,dt} + \overline{\delta}^e_{r,dt} = 0 \qquad \forall d,t \tag{A.4}$$

$$IC_r - \sum_d W_d \sum_t \overline{\delta}^e_{r,dt} A_{r,dt} - \overline{\delta}^c_r = 0 \tag{A.5}$$

$$-cap_r A_{r,dt} + e_{r,dt} \leq 0 \qquad \forall d,t \tag{A.6}$$

$$-e_{r,dt} \leq 0 \qquad \forall d,t \tag{A.7}$$

$$-y_r \leq 0 \tag{A.8}$$

$$\overline{\delta}^e_{r,dt} \geq 0 \qquad \forall d,t \tag{A.9}$$

$$\underline{\delta}^e_{r,dt} \geq 0 \qquad \forall d,t \tag{A.10}$$

$$\overline{\delta}^c_r \geq 0 \tag{A.11}$$

$$-e_{r,dt} \cdot \underline{\delta}^e_{r,dt} = 0 \qquad \forall d,t \tag{A.12}$$

$$-(cap_r A_{r,dt} - e_{r,dt}) \cdot \overline{\delta}^e_{r,dt} = 0 \qquad \forall d,t \tag{A.13}$$

$$-cap_r \cdot \overline{\delta}^c_r = 0 \tag{A.14}$$

A.2. Hydrogen-fired turbines generators optimization problem

Decision variables: $\chi_f = (h_{f,dt}, e_{f,dt}, cap_f)$

$$\max_{\chi_f \in X_f} \quad \Pi_f(\chi_f, \lambda^e_{dt}, \lambda^{H_2}_{dt}) = \sum_d W_d \sum_t [(\lambda^e_{dt} - VC_f)e_{f,dt} - \lambda^{H_2}_t h_{f,dt}] - cap_f IC_f \tag{A.15}$$

where $e_{f,dt} = \eta_f h_{f,dt}$

$$\text{subject to} \quad 0 \le e_{f,dt} \le cap_f \qquad (\underline{\delta}^e_{f,dt}, \overline{\delta}^e_{f,dt}) \qquad \forall t \tag{A.16}$$

$$0 \le cap_f \qquad (\overline{\delta}^c_f) \tag{A.17}$$

Rewriting this optimization problem with the KKT conditions:

$$-W_d(\lambda^e_{dt} - VC_f - \frac{\lambda^{H_2}_{dt}}{\eta_f}) - \underline{\delta}^e_{f,dt} + \overline{\delta}^e_{f,dt} = 0 \qquad \forall d,t \tag{A.18}$$

$$IC_f - \sum_d W_d \sum_t \overline{\delta}^e_{f,dt} - \overline{\delta}^c_f = 0 \tag{A.19}$$

$$-cap_f + e_{f,dt} \le 0 \qquad \forall d,t \tag{A.20}$$

$$-e_{f,dt} \le 0 \qquad \forall d,t \tag{A.21}$$

$$-cap_f \le 0 \tag{A.22}$$

$$\overline{\delta}^e_{f,dt} \ge 0 \qquad \forall d,t \tag{A.23}$$

$$\underline{\delta}^e_{f,dt} \ge 0 \qquad \forall d,t \tag{A.24}$$

$$\overline{\delta}^c_f \ge 0 \tag{A.25}$$

$$-e_{f,dt} \cdot \underline{\delta}^e_{f,dt} = 0 \qquad \forall d,t \tag{A.26}$$

$$-(cap_r - e_{f,dt}) \cdot \overline{\delta}^e_{f,dt} = 0 \qquad \forall d,t \tag{A.27}$$

$$-cap_f \cdot \overline{\delta}^c_f = 0 \tag{A.28}$$

A.3. Electrolyzers optimization problem

Decision variables: $\chi_{ez} = (h_{ez,dt}, e_{ez,dt}, cap_{ez})$

$$\max_{\chi_{ez} \in X_{ez}} \quad \Pi_{ez}(\chi_{ez}, \lambda^e_{dt}, \lambda^{H_2}_{dt}) = \sum_d W_d \sum_t [(\lambda^{H_2}_{dt} - VC_{ez})h_{ez,dt} - \lambda^e_{dt} e_{ez,dt}] - cap_{ez} IC_{ez} \tag{A.29}$$

where $h_{ez,dt} = \eta_{ez} e_{ez,dt}$

$$\text{subject to} \quad 0 \le e_{ez,dt} \le cap_{ez} \qquad (\underline{\delta}^e_{ez,dt}, \overline{\delta}^e_{ez,dt}) \qquad \forall d,t \tag{A.30}$$

$$0 \le cap_{ez} \qquad (\overline{\delta}^c_{ez}) \tag{A.31}$$

Rewriting this optimization problem with the KKT conditions:

$$-W_d[(\lambda^{H_2}_{dt} - VC_{ez})\eta_{ez} - \lambda^e_{dt}] - \underline{\delta}^e_{ez,dt} + \overline{\delta}^e_{ez,dt} = 0 \qquad \forall d,t \tag{A.32}$$

$$IC_{ez} - \sum_d W_d \sum_t \overline{\delta}^e_{ez,dt} - \overline{\delta}^c_{ez} = 0 \tag{A.33}$$

$$-cap_{ez} + e_{ez,dt} \le 0 \qquad \forall d,t \tag{A.34}$$

$$-e_{ez,dt} \le 0 \qquad \forall d,t \tag{A.35}$$

$$-cap_{ez} \le 0 \tag{A.36}$$

$$\overline{\delta}^e_{ez,dt} \ge 0 \qquad \forall d,t \tag{A.37}$$

$$\underline{\delta}^e_{ez,dt} \ge 0 \qquad \forall d,t \tag{A.38}$$

$$\overline{\delta}^c_{ez} \ge 0 \tag{A.39}$$

$$-e_{ez,dt} \cdot \underline{\delta}^e_{ez,dt} = 0 \qquad \forall d,t \tag{A.40}$$

$$-(cap_{ez} - e_{ez,dt}) \cdot \overline{\delta}^e_{ez,dt} = 0 \qquad \forall d,t \tag{A.41}$$

$$-cap_f \cdot \overline{\delta}^c_{ez} = 0 \tag{A.42}$$

A.4. Hydrogen storage optimization problem

Decision variables: $\chi_s = (dh_{dt}, ch_{dt}, P, V, SOC_{dt})$

$$\max_{\chi_s \in X_s} \quad \Pi_s(\chi_s, \lambda^{H_2}_{dt}) = \sum_d W_d \sum_t (\lambda^{H_2}_{dt} - VC_s) dh_{dt} - \sum_d W_d \sum_t (\lambda^{H_2}_{dt} + VC_s) ch_{dt} - P \cdot IC_P - V \cdot IC_V \tag{A.43}$$

Let's define an auxiliary variable Δ that represents the daily energy exchange of the storage of the day d:

$$\Delta h_d = \sum_{t \in T} (\eta_{ch} ch_{dt} - dh_{dt}/\eta_{dh}) \qquad (\gamma_\Delta) \qquad \forall d \tag{A.44}$$

It is now possible to define the base state of charge SOC^0 for all the days of the year.

$$SOC^0_{ad} = SOC^0_{ad-1} + \sum_{d \in D} V_{ad,d} \cdot \Delta h_d \qquad (\gamma_{SOC^0_{ad}}) \qquad \forall ad(2:end) \tag{A.45}$$

where AD represents the set of all days of the year, both representative and non-representative, while $V_{ad,d}$ is the ordering matrix that contains the coefficients of the linear combination of representative days to obtain the set of all days.

It is possible then to define the maximum positive and negative deviations from the base state of charge for representative periods:

$$0 \leq \Delta h_d^{max} \geq SOC_{dt} - SOC_d^0 \qquad (\underline{\delta}_{max,dt}, \overline{\delta}_{max,dt}) \qquad \forall d, t \tag{A.46}$$
$$0 \leq \Delta h_d^{min} \geq SOC_d^0 - SOC_{dt} \qquad (\underline{\delta}_{min,dt}, \overline{\delta}_{min,dt}) \qquad \forall d, t \tag{A.47}$$

And therefore to extend this definition to all the periods:

$$\Delta h_{ad}^{max} = \sum_{d \in D} V_{ad,d} \Delta h_d^{max} \qquad (\gamma_{max,ad}) \qquad \forall ad \tag{A.48}$$
$$\Delta h_{ad}^{min} = \sum_{d \in D} V_{ad,d} \Delta h_d^{min} \qquad (\gamma_{min,ad}) \qquad \forall ad \tag{A.49}$$

At this point, it is possible to impose the state of charge limits for all days:

$$SOC_{ad}^0 + \Delta h_{ad}^{max} \leq V \qquad (\delta_{max,ad,lim}) \qquad \forall ad \tag{A.50}$$
$$SOC_{ad}^0 - \Delta h_{ad}^{min} \geq 0 \qquad (\delta_{min,ad,lim}) \qquad \forall ad \tag{A.51}$$

Finally, a cyclic constraint is added to ensure the final state of charge is greater than the initial one:

$$SOC_{ad_0}^0 \leq SOC_{ad_{end}}^0 + \sum_{d \in D} V_{ad_{end},d} \cdot \Delta h_d \qquad (\delta_{cycle}) \tag{A.52}$$

The basic constraints for the storage problem are the following:

subject to

$$0 \leq dh_{dt} \leq P \qquad (\underline{\delta}_{dh,dt}, \overline{\delta}_{dh,dt}) \qquad \forall d, t \tag{A.53}$$
$$0 \leq ch_{dt} \leq P \qquad (\underline{\delta}_{ch,dt}, \overline{\delta}_{ch,dt}) \qquad \forall d, t \tag{A.54}$$
$$0 \leq P \qquad (\overline{\delta}_P) \tag{A.55}$$
$$0 \leq V \qquad (\overline{\delta}_V) \tag{A.56}$$
$$0 \leq SOC_{dt} \leq V \qquad (\underline{\delta}_{SOC,dt}, \overline{\delta}_{SOC,dt}) \qquad \forall d, t \tag{A.57}$$
$$0 \leq SOC_d^0 \leq V \qquad (\underline{\delta}_{SOC_d^0}, \overline{\delta}_{SOC_d^0}) \qquad \forall d \tag{A.58}$$
$$SOC_{dt} = SOC_{dt-1} + \eta_{ch} ch_{dt} - dh_{dt}/\eta_{dh} \qquad (\beta_{dt}) \qquad \forall d, t \tag{A.59}$$

Rewriting this optimization problem with the KKT conditions:

$$-W_d(\lambda_{dt}^{H_2} - VC_s) - \underline{\delta}_{dh,dt} + \overline{\delta}_{dh,dt} + \frac{\gamma_\Delta}{\eta_{dh}} + \frac{\beta_t}{\eta_{dh}} = 0 \qquad \forall d,t \tag{A.60}$$

$$W_d(\lambda_{dt}^{H_2} + VC_s) - \underline{\delta}_{ch,dt} + \overline{\delta}_{ch,dt} - \gamma_\Delta\eta_{ch} - \beta_t\eta_{ch} = 0 \qquad \forall d,t \tag{A.61}$$

$$IC_P - \sum_d W_d \sum_t (\overline{\delta}_{dh,dt} + \overline{\delta}_{ch,dt}) - \overline{\delta}_P = 0 \tag{A.62}$$

$$IC_V - \sum_d W_d \sum_t (\overline{\delta}_{SOC,dt} + \overline{\delta}_{SOC_d^0}) - \delta_V - \sum_{ad} \delta_{max,ad,lim} = 0 \tag{A.63}$$

$$\overline{\delta}_{max,dt} - \overline{\delta}_{min,dt} - \delta_{SOC,dt} + \overline{\delta}_{SOC,dt} + \beta_{dt} - \beta_{dt-1} = 0 \qquad \forall d,t \tag{A.64}$$

$$\gamma_\Delta - V_{ad,d}\gamma_{SOC_{ad}^0} - V_{ad,d}\delta_{cycle} = 0 \qquad \forall d \tag{A.65}$$

$$\delta_{max,ad,lim} - \delta_{min,ad,lim} + \delta_{cycle} = 0 \qquad ad = 1 \tag{A.66}$$

$$\gamma_{SOC_{ad}^0} - \gamma_{SOC_{ad-1}^0} + \delta_{max,ad,lim} - \delta_{min,ad,lim} = 0 \qquad \forall ad(2:end-1) \tag{A.67}$$

$$\gamma_{SOC_{ad}^0} - \gamma_{SOC_{ad-1}^0} + \delta_{max,ad,lim} - \delta_{min,ad,lim} - \delta_{cycle} = 0 \qquad ad = end \tag{A.68}$$

$$-\underline{\delta}_{max,dt} - \overline{\delta}_{max,dt} - V_{ad,d}\gamma_{max,ad} = 0 \qquad \forall d,t \tag{A.69}$$

$$-\underline{\delta}_{min,dt} - \overline{\delta}_{min,dt} - V_{ad,d}\gamma_{min,ad} = 0 \qquad \forall d,t \tag{A.70}$$

$$\gamma_{max,ad} + \delta_{max,ad,lim} = 0 \qquad \forall ad \tag{A.71}$$

$$\gamma_{min,ad} + \delta_{min,ad,lim} = 0 \qquad \forall ad \tag{A.72}$$

$$-\overline{\delta}_{max,dt} + \overline{\delta}_{min,dt} - \underline{\delta}_{SOC_d^0} + \overline{\delta}_{SOC_d^0} = 0 \qquad \forall d,t \tag{A.73}$$

$$\Delta h_d - \textstyle\sum_{t\in T}(\eta_{ch}ch_{dt} - dh_{dt}/\eta_{dh}) = 0 \qquad \forall d \tag{A.74}$$

$$SOC_{ad}^0 - SOC_{ad-1}^0 - \textstyle\sum_{d\in D} V_{ad,d} * \Delta h_d = 0 \qquad \forall ad(2:end) \tag{A.75}$$

$$\Delta h_{ad}^{max} - \textstyle\sum_{d\in D} V_{ad,d}\Delta h_d^{max} = 0 \qquad \forall ad \tag{A.76}$$

$$\Delta h_{ad}^{min} - \textstyle\sum_{d\in D} V_{ad,d}\Delta h_d^{min} = 0 \qquad \forall ad \tag{A.77}$$

$$SOC_{dt} - SOC_{dt-1} - \eta_{ch}ch_{dt} + dh_{dt}/\eta_{dh} = 0 \qquad \forall d,t \tag{A.78}$$

$$-\Delta h_d^{max} \leq 0 \qquad \forall d,t \tag{A.79}$$

$$\underline{\delta}_{max,dt} \geq 0 \qquad \forall d,t \tag{A.80}$$

$$-\Delta h_d^{max} \cdot \underline{\delta}_{max,dt} = 0 \qquad \forall d,t \tag{A.81}$$

$$SOC_{dt} - SOC_d^0 - \Delta h_d^{max} \leq 0 \qquad \forall d,t \tag{A.82}$$

$$\overline{\delta}_{max,dt} \geq 0 \qquad \forall d,t \tag{A.83}$$

$$(SOC_{dt} - SOC_d^0 - \Delta h_d^{max}) \cdot \overline{\delta}_{max,dt} = 0 \qquad \forall d,t \tag{A.84}$$

$$-\Delta h_d^{min} \leq 0 \qquad \forall d,t \tag{A.85}$$

$$\underline{\delta}_{min,dt} \geq 0 \qquad \forall d,t \tag{A.86}$$

$$-\Delta h_d^{min} \cdot \overline{\delta}_{min,dt} = 0 \qquad \forall d,t \tag{A.87}$$

$$SOC_{ad}^0 + \Delta h_{ad}^{max} - V \leq 0 \qquad \forall ad \tag{A.88}$$

$$\delta_{max,ad,lim} \geq 0 \qquad \forall ad \tag{A.89}$$

$$(SOC_{ad}^0 + \Delta h_{ad}^{max} - V) \cdot \delta_{max,ad,lim} = 0 \qquad \forall ad \tag{A.90}$$

$$-(SOC_{ad}^0 - \Delta h_{ad}^{min}) \leq 0 \qquad \forall ad \tag{A.91}$$

$$\delta_{min,ad,lim} \geq 0 \qquad \forall ad \tag{A.92}$$

$$-(SOC_{ad}^0 - \Delta h_{ad}^{min}) \cdot \delta_{min,ad,lim} = 0 \qquad \forall ad \tag{A.93}$$

$$SOC_{ad_0}^0 - SOC_{ad_{end}}^0 - \textstyle\sum_{d\in D} V_{ad_{end},d} \cdot \Delta h_d \leq 0 \tag{A.94}$$

$$\delta_{cycle} \geq 0 \tag{A.95}$$

$$(SOC_{ad_0}^0 - SOC_{ad_{end}}^0 - \textstyle\sum_{d\in D} V_{ad_{end},d} \cdot \Delta h_d) \cdot \delta_{cycle} = 0 \tag{A.96}$$

$$-dh_{dt} \leq 0 \qquad \forall d,t \tag{A.97}$$

$$\underline{\delta}_{dh,dt} \geq 0 \qquad \forall d,t \tag{A.98}$$

$$-dh_{dt} \cdot \underline{\delta}_{dh,dt} = 0 \qquad \forall d,t \tag{A.99}$$

$$dh_{dt} - P \leq 0 \qquad \forall d,t \tag{A.100}$$

$$\overline{\delta}_{dh,dt} \geq 0 \qquad \forall d,t \tag{A.101}$$

$$(dh_{dt} - P) \cdot \overline{\delta}_{dh,dt} = 0 \qquad \forall d,t \tag{A.102}$$
$$-ch_{dt} \leq 0 \qquad \forall d,t \tag{A.103}$$
$$\underline{\delta}_{ch,dt} \geq 0 \qquad \forall d,t \tag{A.104}$$
$$-ch_{dt} \cdot \underline{\delta}_{ch,dt} = 0 \qquad \forall d,t \tag{A.105}$$
$$ch_{dt} - P \leq 0 \qquad \forall d,t \tag{A.106}$$
$$\overline{\delta}_{ch,dt} \geq 0 \qquad \forall d,t \tag{A.107}$$
$$(ch_{dt} - P) \cdot \overline{\delta}_{ch,dt} = 0 \qquad \forall d,t \tag{A.108}$$
$$-P \leq 0 \tag{A.109}$$
$$\overline{\delta}_{P} \geq 0 \tag{A.110}$$
$$-P \cdot \overline{\delta}_{P} = 0 \tag{A.111}$$
$$-V \leq 0 \tag{A.112}$$
$$\overline{\delta}_{V} \geq 0 \tag{A.113}$$
$$-V \cdot \overline{\delta}_{V} = 0 \tag{A.114}$$
$$-SOC_{dt} \leq 0 \qquad \forall d,t \tag{A.115}$$
$$\underline{\delta}_{SOC,dt} \geq 0 \qquad \forall d,t \tag{A.116}$$
$$-SOC_{dt} \cdot \underline{\delta}_{SOC,dt} = 0 \qquad \forall d,t \tag{A.117}$$
$$SOC_{dt} - V \leq 0 \qquad \forall d,t \tag{A.118}$$
$$\overline{\delta}_{SOC,dt} \geq 0 \qquad \forall d,t \tag{A.119}$$
$$(SOC_{dt} - V) \cdot \overline{\delta}_{SOC,dt} = 0 \qquad \forall d,t \tag{A.120}$$
$$-SOC_d^0 \leq 0 \qquad \forall d \tag{A.121}$$
$$\underline{\delta}_{SOC_d^0} \geq 0 \qquad \forall d \tag{A.122}$$
$$-SOC_d^0 \cdot \underline{\delta}_{SOC_d^0} = 0 \qquad \forall d \tag{A.123}$$
$$SOC_d^0 - V \leq 0 \qquad \forall d \tag{A.124}$$
$$\overline{\delta}_{SOC_d^0} \geq 0 \qquad \forall d \tag{A.125}$$
$$(SOC_d^0 - V) \cdot \overline{\delta}_{SOC_d^0} = 0 \qquad \forall d \tag{A.126}$$
$$\gamma_{\Delta} \quad \text{free} \qquad \forall d \tag{A.127}$$
$$\gamma_{SOC_{ad}^0} \quad \text{free} \qquad \forall ad \tag{A.128}$$
$$\gamma_{max,ad} \quad \text{free} \qquad \forall ad \tag{A.129}$$
$$\gamma_{min,ad} \quad \text{free} \qquad \forall ad \tag{A.130}$$
$$\beta_{dt} \quad \text{free} \qquad \forall d,t \tag{A.131}$$

A.5. Electricity consumers optimization problem

Specify the definition of the elastic section and the fact that is dependent on the timestep, as it is computed by hourly data.

$\chi_{co,e} = (e_{co,dt})$

$$\max_{\chi_{co,e} \in X_{co,e}} \quad \sum_d W_d \sum_t [(WTP^e e_{co,dt} - (e^{ela}_{co,dt})^2 \frac{WTP^e}{2D^e_{ela,dt}}) - \lambda^e_{dt} e_{co,dt}] \tag{A.132}$$

where $D^e_{ela,dt} = \frac{WTP^e}{m}$ is the maximum quantity of demand that is price elastic.

$$\text{subject to} \quad 0 \leq e^{WTP}_{co,dt} \leq 0.8D^e_{dt} \quad (\underline{\mu}^{WTP}_{dt}, \overline{\mu}^{WTP}_{dt}) \quad \forall d,t \tag{A.133}$$
$$0 \leq e^{ela}_{co,dt} \leq D^e_{ela,dt} \quad (\underline{\mu}^{ela}_{dt}, \overline{\mu}^{ela}_{dt}) \quad \forall d,t \tag{A.134}$$
$$\tag{A.135}$$

$$\text{where} \quad e_{co,dt} = e^{WTP}_{co,dt} + e^{ela}_{co,dt} \tag{A.136}$$

Rewriting this optimization problem with its KKT conditions:

$$-W_d(WTP^e - \lambda^e_{dt}) - \underline{\mu}^{WTP}_{dt} + \overline{\mu}^{WTP}_{dt} = 0 \quad \forall d,t \tag{A.137}$$
$$-W_d(WTP^e - \lambda^e_{dt} - 2e^{ela}_{co,dt}\frac{WTP}{2D^e_{ela,dt}}) - \underline{\mu}^{ela}_{dt} + \overline{\mu}^{ela}_{dt} = 0 \quad \forall d,t \tag{A.138}$$
$$e^{WTP}_{co,dt} - 0.8D^e_{dt} \leq 0 \quad \forall d,t \tag{A.139}$$
$$-e^{WTP}_{co,dt} \leq 0 \quad \forall d,t \tag{A.140}$$
$$e^{ela}_{co,dt} - D^e_{ela,dt} \leq 0 \quad \forall d,t \tag{A.141}$$
$$-e^{ela}_{co,dt} \leq 0 \quad \forall d,t \tag{A.142}$$
$$\overline{\mu}^{WTP}_{dt} \geq 0 \quad \forall d,t \tag{A.143}$$
$$\underline{\mu}^{WTP}_{dt} \geq 0 \quad \forall d,t \tag{A.144}$$
$$\overline{\mu}^{ela}_{dt} \geq 0 \quad \forall d,t \tag{A.145}$$
$$\underline{\mu}^{ela}_{dt} \geq 0 \quad \forall d,t \tag{A.146}$$
$$-(-e^{WTP}_{co,dt} + 0.8D^e_{dt}) \cdot \overline{\mu}^{WTP}_{dt} = 0 \quad \forall d,t \tag{A.147}$$
$$-e^{WTP}_{co,dt} \cdot \underline{\mu}^{WTP}_{dt} = 0 \quad \forall d,t \tag{A.148}$$
$$-(-e^{ela}_{co,dt} + D^e_{ela,dt}) \cdot \overline{\mu}^{ela}_{dt} = 0 \quad \forall d,t \tag{A.149}$$
$$-e^{ela}_{co,dt} \cdot \underline{\mu}^{ela}_{dt} = 0 \quad \forall d,t \tag{A.150}$$

A.6. Hydrogen consumers optimization problem

Here the elastic section is computed only once, as the slope of the hydrogen demand is computed as the average slope of the electricity demand.
$\chi_{co,h} = (h_{co,dt})$

$$\max_{\chi_{co,h} \in X_{co,h}} \quad \sum_d W_d \sum_t [(WTP^{H_2} h_{co,dt} - (h^{ela}_{co,dt})^2 \frac{WTP^{H_2}}{2D^{H_2}_{ela}}) - \lambda^{H_2}_{dt} h_{co,dt}] \tag{A.151}$$

$$\text{subject to} \quad 0 \leq h^{WTP}_{co,dt} \leq 0.8D^{H_2}_{dt} \quad (\underline{\mu}^{WTP,H_2}_{dt}, \overline{\mu}^{WTP,H_2}_{dt}) \quad \forall d,t \tag{A.152}$$
$$0 \leq h^{ela}_{co,dt} \leq D^{H_2}_{ela} \quad (\underline{\mu}^{ela,H_2}_{dt}, \overline{\mu}^{ela,H_2}_{dt}) \quad \forall d,t \tag{A.153}$$
$$\tag{A.154}$$

$$\text{where} \quad h_{co,dt} = h^{WTP}_{co,dt} + h^{ela}_{co,dt} \tag{A.155}$$

Rewriting this optimization problem with its KKT conditions:

$$-W_d(WTP^{H_2} - \lambda_{dt}^{H_2}) - \underline{\mu}_{dt}^{WTP,H_2} + \overline{\mu}_{dt}^{WTP,H_2} = 0 \qquad \forall d,t \qquad \text{(A.156)}$$

$$-W_d(WTP^{H_2} - \lambda_{dt}^{H_2} - 2h_{co,dt}^{ela}\frac{WTP^{H_2}}{2D_{ela}^{H_2}}) - \underline{\mu}_{dt}^{ela,H_2} + \overline{\mu}_{dt}^{ela,H_2} = 0 \qquad \forall d,t \qquad \text{(A.157)}$$

$$h_{co,dt}^{WTP} - 0.8D_{dt}^{H_2} \leq 0 \qquad \forall d,t \qquad \text{(A.158)}$$

$$-h_{co,dt}^{WTP} \leq 0 \qquad \forall d,t \qquad \text{(A.159)}$$

$$h_{co,dt}^{ela} - D_{ela,dt}^{H_2} \leq 0 \qquad \forall d,t \qquad \text{(A.160)}$$

$$-h_{co,dt}^{ela} \leq 0 \qquad \forall d,t \qquad \text{(A.161)}$$

$$\overline{\mu}_{dt}^{WTP,H_2} \geq 0 \qquad \forall d,t \qquad \text{(A.162)}$$

$$\underline{\mu}_{dt}^{WTP,H_2} \geq 0 \qquad \forall d,t \qquad \text{(A.163)}$$

$$\overline{\mu}_{dt}^{ela,H_2} \geq 0 \qquad \forall d,t \qquad \text{(A.164)}$$

$$\underline{\mu}_{dt}^{ela,H_2} \geq 0 \qquad \forall d,t \qquad \text{(A.165)}$$

$$-(-h_{co,dt}^{WTP} + 0.8D_{dt}^{H_2}) \cdot \overline{\mu}_{dt}^{WTP,H_2} = 0 \qquad \forall d,t \qquad \text{(A.166)}$$

$$-h_{co,dt}^{WTP} \cdot \underline{\mu}_{dt}^{WTP,H_2} = 0 \qquad \forall d,t \qquad \text{(A.167)}$$

$$-(-h_{co,dt}^{ela} + D_{ela,dt}^{H_2}) \cdot \overline{\mu}_{dt}^{ela,H_2} = 0 \qquad \forall d,t \qquad \text{(A.168)}$$

$$-h_{co,dt}^{ela} \cdot \underline{\mu}_{dt}^{ela,H_2} = 0 \qquad \forall d,t \qquad \text{(A.169)}$$

A.7. Market clearing constraints

$$\sum_r e_{r,dt} + e_{f,dt} - e_{co,dt} - e_{ez,dt} = 0 \qquad ({\lambda'}_{dt}^{e}) \qquad \forall d,t \qquad \text{(A.170)}$$

$$h_{ez,dt} + dh_{dt} - ch_{dt} - h_{co,dt} - h_{f,dt} = 0 \qquad ({\lambda'}_{dt}^{H_2}) \qquad \forall d,t \qquad \text{(A.171)}$$

B
Equivalent Optimization Problem

Oss: VC (variable costs) do not appear for electrolysis and storage as they are set to zero

$$
\begin{aligned}
\max_{\chi \in X} \quad SW(\chi) = & \sum_d W_d \sum_t [WTP^e e_{co,dt} - (e^{ela}_{co,dt})^2 \frac{WTP^e}{2D^e_{ela,dt}}] + \\
& + \sum_d W_d \sum_t [WTP^{H_2} h_{co,dt} - (h^{ela}_{co,dt})^2 \frac{WTP^{H_2}}{2D^{H_2}_{ela}}] + \\
& - \sum_r \sum_d W_d \sum_t VC_r e_{r,dt} - \sum_d W_d \sum_t VC_f e_{h,dt} + \\
& - \sum_d W_d \sum_t VC_{ez} h_{ez,dt} - \sum_d W_d \sum_t VC_s (ch_{,dt} + dh_{dt}) + \\
& - \sum_r IC_r cap_r - IC_f cap_f - IC_{ez} cap_{ez} - IC_P P - IC_V V
\end{aligned}
\tag{B.1}
$$

subject to:

Market balances constraints

$$\sum_r e_{r,dt} + e_{h,dt} - e_{ez,dt} - e_{co,dt} = 0 \qquad (\lambda^e_{dt}) \qquad \forall d,t \tag{B.2}$$

$$h_{ez,dt} + dh_{dt} - ch_{dt} - h_{f,dt} - h_{co,dt} = 0 \qquad (\lambda^{H_2}_{dt}) \qquad \forall d,t \tag{B.3}$$

Electricity generator constraints

$$0 \leq g_{r,dt} \leq A_{r,dt} cap_r \qquad (\underline{\delta}^e_{r,dt}, \overline{\delta}^e_{r,dt}) \qquad \forall r,d,t \tag{B.4}$$

$$0 \leq g_{f,dt} \leq cap_f \qquad (\underline{\delta}^e_{f,dt}, \overline{\delta}^e_{f,dt}) \qquad \forall d,t \tag{B.5}$$

$$0 \leq cap_r \qquad (\overline{\delta}^c_r) \qquad \forall r \tag{B.6}$$

$$0 \leq cap_c \qquad (\overline{\delta}^c_f) \tag{B.7}$$

Demand agents constraints

$$0 \leq e^{WTP}_{co,dt} \leq 0.8D^{e}_{dt} \qquad (\underline{\mu}^{WTP}_{dt}, \overline{\mu}^{WTP}_{dt}) \qquad \forall d,t \tag{B.8}$$
$$0 \leq e^{ela}_{co,dt} \leq D^{e}_{ela,dt} \qquad (\underline{\mu}^{ela}_{dt}, \overline{\mu}^{ela}_{dt}) \qquad \forall d,t \tag{B.9}$$
$$0 \leq h^{WTP}_{co,dt} \leq 0.8D^{H_2}_{dt} \qquad (\underline{\mu}^{WTP,H_2}_{dt}, \overline{\mu}^{WTP,H_2}_{dt}) \qquad \forall d,t \tag{B.10}$$
$$0 \leq h^{ela}_{co,dt} \leq D^{H_2}_{ela} \qquad (\underline{\mu}^{ela,H_2}_{dt}, \overline{\mu}^{ela,H_2}_{dt}) \qquad \forall d,t \tag{B.11}$$

Electrolyzers constraints

$$0 \leq e_{ez,dt} \leq cap_{ez} \qquad (\underline{\delta}^{e}_{ez,dt}, \overline{\delta}^{e}_{ez,dt}) \qquad \forall d,t \tag{B.12}$$
$$0 \leq cap_{ez} \qquad (\overline{\delta}^{c}_{ez}) \tag{B.13}$$

Hydrogen storage constraints

$$0 \leq dh_{dt} \leq P \qquad (\underline{\delta}_{dh,dt}, \overline{\delta}_{dh,dt}) \qquad \forall d,t \tag{B.14}$$
$$0 \leq ch_{dt} \leq P \qquad (\underline{\delta}_{ch,dt}, \overline{\delta}_{ch,dt}) \qquad \forall d,t \tag{B.15}$$
$$0 \leq P \qquad (\overline{\delta}_{P}) \tag{B.16}$$
$$0 \leq V \qquad (\overline{\delta}_{V}) \tag{B.17}$$
$$0 \leq SOC_{dt} \leq V \qquad (\underline{\delta}_{SOC,dt}, \overline{\delta}_{SOC,dt}) \qquad \forall d,t \tag{B.18}$$
$$0 \leq SOC^{0}_{d} \leq V \qquad (\underline{\delta}_{SOC^{0}_{d}}, \overline{\delta}_{SOC^{0}_{d}}) \qquad \forall d \tag{B.19}$$
$$SOC_{dt} = SOC_{dt-1} + \eta_{ch} ch_{dt} - dh_{dt}/\eta_{dh} \qquad (\beta_{dt}) \qquad \forall d,t \tag{B.20}$$
$$\Delta h_{d} = \sum_{t \in T} (\eta_{ch} ch_{dt} - dh_{dt}/\eta_{dh}) \qquad (\gamma_{\Delta}) \qquad \forall d \tag{B.21}$$
$$SOC^{0}_{ad} = SOC^{0}_{ad-1} + \sum_{d \in D} V_{ad,d} \cdot \Delta h_{d} \qquad (\gamma_{SOC^{0}_{ad}}) \qquad \forall ad(2:end) \tag{B.22}$$
$$0 \leq \Delta h^{max}_{d} \geq SOC_{dt} - SOC^{0}_{d} \qquad (\underline{\delta}_{max,dt}, \overline{\delta}_{max,dt}) \qquad \forall d,t \tag{B.23}$$
$$0 \leq \Delta h^{min}_{d} \geq SOC^{0}_{d} - SOC_{dt} \qquad (\underline{\delta}_{min,dt}, \overline{\delta}_{min,dt}) \qquad \forall d,t \tag{B.24}$$
$$\Delta h^{max}_{ad} = \sum_{d \in D} V_{ad,d} \Delta h^{max}_{d} \qquad (\gamma_{max,ad}) \qquad \forall ad \tag{B.25}$$
$$\Delta h^{min}_{ad} = \sum_{d \in D} V_{ad,d} \Delta h^{min}_{d} \qquad (\gamma_{min,ad}) \qquad \forall ad \tag{B.26}$$
$$SOC^{0}_{ad} + \Delta h^{max}_{ad} \leq V \qquad (\delta_{max,ad,lim}) \qquad \forall ad \tag{B.27}$$
$$SOC^{0}_{ad} - \Delta h^{min}_{ad} \geq 0 \qquad (\delta_{min,ad,lim}) \qquad \forall ad \tag{B.28}$$
$$SOC^{0}_{ad_0} \leq SOC^{0}_{ad_{end}} + \sum_{d \in D} V_{ad_{end},d} \cdot \Delta h_{d} \qquad (\delta_{cycle}) \tag{B.29}$$

Rewriting this optimization problem with its KKT conditions:

$$W_d VC_r + \lambda^e_{dt} - \underline{\delta}^e_{r,dt} + \overline{\delta}^e_{r,dt} = 0 \qquad \forall d,t \tag{B.30}$$

$$IC_r - \sum_d W_d \sum_t \overline{\delta}^e_{r,dt} A_{r,dt} - \overline{\delta}^c_r = 0 \tag{B.31}$$

$$+ W_d VC_f + \lambda^e_{dt} - \frac{\lambda^{H_2}_{dt}}{\eta_f} - \underline{\delta}^e_{f,dt} + \overline{\delta}^e_{f,dt} = 0 \qquad \forall d,t \tag{B.32}$$

$$IC_f - \sum_d W_d \sum_t \overline{\delta}^e_{f,dt} - \overline{\delta}^c_f = 0 \tag{B.33}$$

$$W_d VC_{ez} \eta_{ez} + \eta_{ez} \lambda^{H_2}_{dt} - \lambda^e_{dt} - \underline{\delta}^e_{ez,dt} + \overline{\delta}^e_{ez,dt} = 0 \qquad \forall d,t \tag{B.34}$$

$$IC_{ez} - \sum_d W_d \sum_t \overline{\delta}^e_{ez,dt} - \overline{\delta}^c_{ez} = 0 \tag{B.35}$$

$$\lambda^{H_2}_{dt} + W_d VC_s - \underline{\delta}_{dh,dt} + \overline{\delta}_{dh,dt} + \frac{\gamma_\Delta}{\eta_{dh}} + \frac{\beta_t}{\eta_{dh}} = 0 \qquad \forall d,t \tag{B.36}$$

$$- \lambda^{H_2}_{dt} + W_d + VC_s - \underline{\delta}_{ch,dt} + \overline{\delta}_{ch,dt} - \gamma_\Delta \eta_{ch} - \beta_t \eta_{ch} = 0 \qquad \forall d,t \tag{B.37}$$

$$IC_P - \sum_d W_d \sum_t (\overline{\delta}_{dh,dt} + \overline{\delta}_{ch,dt}) - \overline{\delta}_P = 0 \tag{B.38}$$

$$IC_V - \sum_d W_d \sum_t (\overline{\delta}_{SOC,dt} + \overline{\delta}_{SOC^0_d}) - \delta_V - \sum_{ad} \delta_{max,ad,lim} = 0 \tag{B.39}$$

$$- W_d WTP^e - \lambda^e_{dt} - \underline{\mu}^{WTP}_{dt} + \overline{\mu}^{WTP}_{dt} = 0 \qquad \forall d,t \tag{B.40}$$

$$- W_d (WTP^e - 2e^{ela}_{co,dt} \frac{WTP}{2D^e_{ela,dt}}) - \lambda^e_{dt} - \underline{\mu}^{ela}_{dt} + \overline{\mu}^{ela}_{dt} = 0 \qquad \forall d,t \tag{B.41}$$

$$- W_d WTP^{H_2} - \lambda^{H_2}_{dt} - \underline{\mu}^{WTP,H_2}_{dt} + \overline{\mu}^{WTP,H_2}_{dt} = 0 \qquad \forall d,t \tag{B.42}$$

$$- W_d (WTP^{H_2} - 2h^{ela}_{co,dt} \frac{WTP^{H_2}}{2D^{H_2}_{ela}}) - \lambda^{H_2}_{dt} - \underline{\mu}^{ela,H_2}_{dt} + \overline{\mu}^{ela,H_2}_{dt} = 0 \qquad \forall d,t \tag{B.43}$$

$$- cap_r A_{r,dt} + e_{r,dt} \leq 0 \qquad \forall d,t \tag{B.44}$$

$$- e_{r,dt} \leq 0 \qquad \forall d,t \tag{B.45}$$

$$- cap_r \leq 0 \tag{B.46}$$

$$\overline{\delta}^e_{r,dt} \geq 0 \qquad \forall d,t \tag{B.47}$$

$$\underline{\delta}^e_{r,dt} \geq 0 \qquad \forall d,t \tag{B.48}$$

$$\overline{\delta}^c_r \geq 0 \tag{B.49}$$

$$- e_{r,dt} \cdot \underline{\delta}^e_{r,dt} = 0 \qquad \forall d,t \tag{B.50}$$

$$- (cap_r A_{r,dt} - e_{r,dt}) \cdot \overline{\delta}^e_{r,dt} = 0 \qquad \forall d,t \tag{B.51}$$

$$- cap_r \cdot \overline{\delta}^c_r = 0 \tag{B.52}$$

$$- cap_f + e_{f,dt} \leq 0 \qquad \forall d,t \tag{B.53}$$

$$- e_{f,dt} \leq 0 \qquad \forall d,t \tag{B.54}$$

$$- cap_f \leq 0 \tag{B.55}$$

$$\overline{\delta}^e_{f,dt} \geq 0 \qquad \forall d,t \tag{B.56}$$

$$\underline{\delta}^e_{f,dt} \geq 0 \qquad \forall d,t \tag{B.57}$$

$$\overline{\delta}^c_f \geq 0 \tag{B.58}$$

$$- e_{f,dt} \cdot \underline{\delta}^e_{f,dt} = 0 \qquad \forall d,t \tag{B.59}$$

$$- (cap_r - e_{f,dt}) \cdot \overline{\delta}^e_{f,dt} = 0 \qquad \forall d,t \tag{B.60}$$

$$- cap_f \cdot \overline{\delta}^c_f = 0 \tag{B.61}$$

$$-cap_{ez} + e_{ez,dt} \leq 0 \quad \forall d,t \tag{B.62}$$
$$-e_{ez,dt} \leq 0 \quad \forall d,t \tag{B.63}$$
$$-cap_{ez} \leq 0 \tag{B.64}$$
$$\overline{\delta}^{e}_{ez,dt} \geq 0 \quad \forall d,t \tag{B.65}$$
$$\underline{\delta}^{e}_{ez,dt} \geq 0 \quad \forall d,t \tag{B.66}$$
$$\overline{\delta}^{c}_{ez} \geq 0 \tag{B.67}$$
$$-e_{ez,dt} \cdot \underline{\delta}^{e}_{ez,dt} = 0 \quad \forall d,t \tag{B.68}$$
$$-(cap_{ez} - e_{ez,dt}) \cdot \overline{\delta}^{e}_{ez,dt} = 0 \quad \forall d,t \tag{B.69}$$
$$-cap_{f} \cdot \overline{\delta}^{c}_{ez} = 0 \tag{B.70}$$
$$\overline{\delta}_{max,dt} - \overline{\delta}_{min,dt} - \underline{\delta}_{SOC,dt} + \overline{\delta}_{SOC,dt} + \beta_{dt} - \beta_{dt-1} = 0 \quad \forall d,t \tag{B.71}$$
$$\gamma_{\Delta} - V_{ad,d}\gamma_{SOC^0_{ad}} - V_{ad,d}\delta_{cycle} = 0 \quad \forall d \tag{B.72}$$
$$\delta_{max,ad,lim} - \delta_{min,ad,lim} + \delta_{cycle} = 0 \quad ad = 1 \tag{B.73}$$
$$\gamma_{SOC^0_{ad}} - \gamma_{SOC^0_{ad-1}} + \delta_{max,ad,lim} - \delta_{min,ad,lim} = 0 \quad \forall ad(2:end-1) \tag{B.74}$$
$$\gamma_{SOC^0_{ad}} - \gamma_{SOC^0_{ad-1}} + \delta_{max,ad,lim} - \delta_{min,ad,lim} - \delta_{cycle} = 0 \quad ad = end \tag{B.75}$$
$$-\underline{\delta}_{max,dt} - \overline{\delta}_{max,dt} - V_{ad,d}\gamma_{max,ad} = 0 \quad \forall d,t \tag{B.76}$$
$$-\underline{\delta}_{min,dt} - \overline{\delta}_{min,dt} - V_{ad,d}\gamma_{min,ad} = 0 \quad \forall d,t \tag{B.77}$$
$$\gamma_{max,ad} + \delta_{max,ad,lim} = 0 \quad \forall ad \tag{B.78}$$
$$\gamma_{min,ad} + \delta_{min,ad,lim} = 0 \quad \forall ad \tag{B.79}$$
$$-\overline{\delta}_{max,dt} + \overline{\delta}_{min,dt} - \underline{\delta}_{SOC^0_d} + \overline{\delta}_{SOC^0_d} = 0 \quad \forall d,t \tag{B.80}$$
$$\Delta h_d - \sum_{t \in T}(\eta_{ch} ch_{dt} - dh_{dt}/\eta_{dh}) = 0 \quad \forall d \tag{B.81}$$
$$SOC^0_{ad} - SOC^0_{ad-1} - \sum_{d \in D} V_{ad,d} \cdot \Delta h_d = 0 \quad \forall ad(2:end) \tag{B.82}$$
$$\Delta h^{max}_{ad} - \sum_{d \in D} V_{ad,d}\Delta h^{max}_d = 0 \quad \forall ad \tag{B.83}$$
$$\Delta h^{min}_{ad} - \sum_{d \in D} V_{ad,d}\Delta h^{min}_d = 0 \quad \forall ad \tag{B.84}$$
$$SOC_{dt} - SOC_{dt-1} - \eta_{ch} ch_{dt} + dh_{dt}/\eta_{dh} = 0 \quad \forall d,t \tag{B.85}$$
$$-\Delta h^{max}_d \leq 0 \quad \forall d,t \tag{B.86}$$
$$\underline{\delta}_{max,dt} \geq 0 \quad \forall d,t \tag{B.87}$$
$$-\Delta h^{max}_d \cdot \underline{\delta}_{max,dt} = 0 \quad \forall d,t \tag{B.88}$$
$$SOC_{dt} - SOC^0_d - \Delta h^{max}_d \leq 0 \quad \forall d,t \tag{B.89}$$
$$\overline{\delta}_{max,dt} \geq 0 \quad \forall d,t \tag{B.90}$$
$$(SOC_{dt} - SOC^0_d - \Delta h^{max}_d) \cdot \overline{\delta}_{max,dt} = 0 \quad \forall d,t \tag{B.91}$$
$$-\Delta h^{min}_d \leq 0 \quad \forall d,t \tag{B.92}$$
$$\underline{\delta}_{min,dt} \geq 0 \quad \forall d,t \tag{B.93}$$
$$-\Delta h^{min}_d \cdot \overline{\delta}_{min,dt} = 0 \quad \forall d,t \tag{B.94}$$
$$SOC^0_{ad} + \Delta h^{max}_{ad} - V \leq 0 \quad \forall ad \tag{B.95}$$
$$\delta_{max,ad,lim} \geq 0 \quad \forall ad \tag{B.96}$$
$$(SOC^0_{ad} + \Delta h^{max}_{ad} - V) \cdot \delta_{max,ad,lim} = 0 \quad \forall ad \tag{B.97}$$
$$-(SOC^0_{ad} - \Delta h^{min}_{ad}) \leq 0 \quad \forall ad \tag{B.98}$$
$$\delta_{min,ad,lim} \geq 0 \quad \forall ad \tag{B.99}$$
$$-(SOC^0_{ad} - \Delta h^{min}_{ad}) \cdot \delta_{min,ad,lim} = 0 \quad \forall ad \tag{B.100}$$
$$SOC^0_{ad_0} - SOC^0_{ad_{end}} - \sum_{d \in D} V_{ad_{end},d} * \Delta h_d \leq 0 \tag{B.101}$$
$$\delta_{cycle} \geq 0 \tag{B.102}$$
$$(SOC^0_{ad_0} - SOC^0_{ad_{end}} - \sum_{d \in D} V_{ad_{end},d} * \Delta h_d) \cdot \delta_{cycle} = 0 \tag{B.103}$$
$$-dh_{dt} \leq 0 \quad \forall d,t \tag{B.104}$$
$$\underline{\delta}_{dh,dt} \geq 0 \quad \forall d,t \tag{B.105}$$

$$- dh_{dt} \cdot \underline{\delta}_{dh,dt} = 0 \quad \forall d,t \quad \text{(B.106)}$$
$$dh_{dt} - P \leq 0 \quad \forall d,t \quad \text{(B.107)}$$
$$\overline{\delta}_{dh,dt} \geq 0 \quad \forall d,t \quad \text{(B.108)}$$
$$(dh_{dt} - P) \cdot \overline{\delta}_{dh,dt} = 0 \quad \forall d,t \quad \text{(B.109)}$$
$$- ch_{dt} \leq 0 \quad \forall d,t \quad \text{(B.110)}$$
$$\underline{\delta}_{ch,dt} \geq 0 \quad \forall d,t \quad \text{(B.111)}$$
$$- ch_{dt} \cdot \underline{\delta}_{ch,dt} = 0 \quad \forall d,t \quad \text{(B.112)}$$
$$ch_{dt} - P \leq 0 \quad \forall d,t \quad \text{(B.113)}$$
$$\overline{\delta}_{ch,dt} \geq 0 \quad \forall d,t \quad \text{(B.114)}$$
$$(ch_{dt} - P) \cdot \overline{\delta}_{ch,dt} = 0 \quad \forall d,t \quad \text{(B.115)}$$
$$- P \leq 0 \quad \text{(B.116)}$$
$$\overline{\delta}_P \geq 0 \quad \text{(B.117)}$$
$$- P \cdot \overline{\delta}_P = 0 \quad \text{(B.118)}$$
$$- V \leq 0 \quad \text{(B.119)}$$
$$\overline{\delta}_V \geq 0 \quad \text{(B.120)}$$
$$- V \cdot \overline{\delta}_V = 0 \quad \text{(B.121)}$$
$$- SOC_{dt} \leq 0 \quad \forall d,t \quad \text{(B.122)}$$
$$\underline{\delta}_{SOC,dt} \geq 0 \quad \forall d,t \quad \text{(B.123)}$$
$$- SOC_{dt} \cdot \underline{\delta}_{SOC,dt} = 0 \quad \forall d,t \quad \text{(B.124)}$$
$$SOC_{dt} - V \leq 0 \quad \forall d,t \quad \text{(B.125)}$$
$$\overline{\delta}_{SOC,dt} \geq 0 \quad \forall d,t \quad \text{(B.126)}$$
$$(SOC_{dt} - V) \cdot \overline{\delta}_{SOC,dt} = 0 \quad \forall d,t \quad \text{(B.127)}$$
$$- SOC_d^0 \leq 0 \quad \forall d \quad \text{(B.128)}$$
$$\underline{\delta}_{SOC_d^0} \geq 0 \quad \forall d \quad \text{(B.129)}$$
$$- SOC_d^0 \cdot \underline{\delta}_{SOC_d^0} = 0 \quad \forall d \quad \text{(B.130)}$$
$$SOC_d^0 - V \leq 0 \quad \forall d \quad \text{(B.131)}$$
$$\overline{\delta}_{SOC_d^0} \geq 0 \quad \forall d \quad \text{(B.132)}$$
$$(SOC_d^0 - V) \cdot \overline{\delta}_{SOC_d^0} = 0 \quad \forall d \quad \text{(B.133)}$$
$$\gamma_\Delta \quad \text{free} \quad \forall d \quad \text{(B.134)}$$
$$\gamma_{SOC_{ad}^0} \quad \text{free} \quad \forall ad \quad \text{(B.135)}$$
$$\gamma_{max,ad} \quad \text{free} \quad \forall ad \quad \text{(B.136)}$$
$$\gamma_{min,ad} \quad \text{free} \quad \forall ad \quad \text{(B.137)}$$
$$\beta_{dt} \quad \text{free} \quad \forall d,t \quad \text{(B.138)}$$
$$e_{co,dt}^{WTP} - 0.8D_{dt}^e \leq 0 \quad \forall d,t \quad \text{(B.139)}$$
$$- e_{co,dt}^{WTP} \leq 0 \quad \forall d,t \quad \text{(B.140)}$$
$$e_{co,dt}^{ela} - D_{ela,dt}^e \leq 0 \quad \forall d,t \quad \text{(B.141)}$$
$$- e_{co,dt}^{ela} \leq 0 \quad \forall d,t \quad \text{(B.142)}$$
$$\overline{\mu}_{dt}^{WTP} \geq 0 \quad \forall d,t \quad \text{(B.143)}$$
$$\underline{\mu}_{dt}^{WTP} \geq 0 \quad \forall d,t \quad \text{(B.144)}$$
$$\overline{\mu}_{dt}^{ela} \geq 0 \quad \forall d,t \quad \text{(B.145)}$$
$$\underline{\mu}_{dt}^{ela} \geq 0 \quad \forall d,t \quad \text{(B.146)}$$
$$- (-e_{co,dt}^{WTP} + 0.8D_{dt}^e) \cdot \overline{\mu}_{dt}^{WTP} = 0 \quad \forall d,t \quad \text{(B.147)}$$

$$- e^{WTP}_{co,dt} \cdot \underline{\mu}^{WTP}_{dt} = 0 \qquad \forall d,t \tag{B.148}$$

$$- (-e^{ela}_{co,dt} + D^{e}_{ela,dt}) \cdot \overline{\mu}^{ela}_{dt} = 0 \qquad \forall d,t \tag{B.149}$$

$$- e^{ela}_{co,dt} \cdot \underline{\mu}^{ela}_{dt} = 0 \qquad \forall d,t \tag{B.150}$$

$$h^{WTP}_{co,dt} - 0.8D^{H_2}_{dt} \leq 0 \qquad \forall d,t \tag{B.151}$$

$$- h^{WTP}_{co,dt} \leq 0 \qquad \forall d,t \tag{B.152}$$

$$h^{ela}_{co,dt} - D^{H_2}_{ela,dt} \leq 0 \qquad \forall d,t \tag{B.153}$$

$$- h^{ela}_{co,dt} \leq 0 \qquad \forall d,t \tag{B.154}$$

$$\overline{\mu}^{WTP,H_2}_{dt} \geq 0 \qquad \forall d,t \tag{B.155}$$

$$\underline{\mu}^{WTP,H_2}_{dt} \geq 0 \qquad \forall d,t \tag{B.156}$$

$$\overline{\mu}^{ela,H_2}_{dt} \geq 0 \qquad \forall d,t \tag{B.157}$$

$$\underline{\mu}^{ela,H_2}_{dt} \geq 0 \qquad \forall d,t \tag{B.158}$$

$$- (-h^{WTP}_{co,dt} + 0.8D^{H_2}_{dt}) \cdot \overline{\mu}^{WTP,H_2}_{dt} = 0 \qquad \forall d,t \tag{B.159}$$

$$- h^{WTP}_{co,dt} \cdot \underline{\mu}^{WTP,H_2}_{dt} = 0 \qquad \forall d,t \tag{B.160}$$

$$- (-h^{ela}_{co,dt} + D^{H_2}_{ela,dt}) \cdot \overline{\mu}^{ela,H_2}_{dt} = 0 \qquad \forall d,t \tag{B.161}$$

$$- h^{ela}_{co,dt} \cdot \underline{\mu}^{ela,H_2}_{dt} = 0 \qquad \forall d,t \tag{B.162}$$