

The impact of contract duration in capacity markets on the long-term capacity mix

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Preface

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Abstract

Capacity markets have become increasingly prevalent across European electricity systems to ensure resource adequacy. Many implementations combine short-term contracts with longer-term contracts for new investments. However, demand response investments are often excluded from long-term contracts, creating asymmetric revenue uncertainty across competing technologies. Despite its influence on technology competition and investment outcomes, this asymmetry has received limited attention in the academic literature.

This thesis investigates the effect of unequal capacity market contract durations on the long-term capacity mix. An equilibrium-based, risk-averse capacity market auction model was developed using uncertainty scenarios derived from a separate economic dispatch model and applied to a case study inspired by the Belgian electricity system. Three contract duration frameworks are compared: one-year contracts for all technologies, the current partially differentiated structure granting fifteen-year contracts to gas-fired capacity and battery storage but not demand response, and a fully equalized fifteen-year contract structure. Intermediate cases in which demand response receives contracts between one and fifteen years are additionally evaluated.

The results show that contract duration design has a significant impact on both the resulting capacity mix and the cleared capacity price. Granting demand response investments access to the same contract durations as other technologies increased their participation in capacity procurement by approximately 34%, while reducing the cleared capacity price by 6.7%. The large price difference between the case without long-term contracts and the case with fifteen-year contracts for all technologies further demonstrates the significant economic value that long-term contracts provide to new investments. Finally, the results show that partially extending demand response contract durations toward those granted to other technologies already captures most of the benefits associated with full fifteen-year contracts, both in reducing capacity prices and increasing the share of demand response within the capacity mix. These findings suggest that policymakers may capture significant benefits from broadening long-term contract eligibility for demand response without requiring full equalization with generation and storage technologies.

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List of abbreviations and symbols

Abbreviations

BESS	Battery energy storage systems
CAPEX	Capital expenditure
CCGT	Combined-cycle gas turbine
CfD	Contract for difference
CHP	Combined heat and power
CD	Contract duration
CM	Capacity market
CRM	Capacity remuneration mechanism
CVaR	Conditional value-at-risk
DR	Demand response
EOM	Energy-only market
ETS	European Union emissions trading system
OCGT	Open-cycle gas turbine
O&M	Operation and maintenance
TSO	Transmission system operator
VOLL	Value of lost load
WTP	Willingness to pay

Symbols

Sets

$c \in C$	Contract duration cases
$e \in E$	Capacity providers eligible for long-term contracts
$i \in I$	Generating units
$j \in J$	Time steps
$k \in K$	Storage units
$ne \in NE$	Capacity providers not eligible for long-term contracts
$p \in P$	Capacity providing units
$s \in S$	EOM scenarios
$s \in tail_p$	Set of critical relative losses
$sc \in SC$	Capacity price scenarios

Variables

b_p	Bid price [€/MW/y]
$c_{k,j}$	Charging power [MW]
C_c	Total producer cost [€/y]
$ccd_{i,j}$	Carbon cost [€/h]
$CE_{ne,s,sc}$	Combined earnings [€/MW/y]
CTC_c	Cost to consumers [€/y]
$CVaR_p$	Conditional value-at-risk [€/MW/y]
$d_{k,j}$	Discharging power [MW]
$e_{k,j}$	State-of-charge [MWh]
$EM_{p,s}$	EOM relative gross profit [€/MW/y]
ens_j	Energy not served [MW]
$fcd_{i,j}$	Fuel cost [€/h]
$g_{i,j}$	Generation [MW]
p_j	Price [€/MWh]
PS_c	Producer surplus [€/y]
R_c	Total producer revenue [€/y]
$ResD_j$	Residual demand [MW]
SC_c	Societal cost [€/y]
x_p	Capacity investment [MW]
δ_p	Binary investment variable (0,1)
λ	Capacity market clearing price [€/MW/y]
Π_p	Gross profit [€]

Parameters

cap_i	Generator capacity [MW]
CD	Contract duration [y]
CI_i	Carbon intensity [tonCO ₂ eq/MWh]
CT	Capacity target [MW]
CPC_p	Capacity profit curve [€/MW ² /y]
E_k	Battery energy capacity [MWh]
F_p	Derating factor [%]
IC_p	Overnight investment cost [€/MW]
M_{big}	Big-M method penalty [-]
$O\&M_i$	Operation and maintenance cost [€/MWh]
p_{gas}	TTF gas price [€/MW _{th}]
P_k	Battery power capacity [MW]
P_s	Probability of scenario [%]
r_p	Discount rate [%]
$VOLL$	Value of lost load [€/MWh]
y_p	Existing capacity [MW]
α	Carbon price [€/tonCO ₂ eq]
β	Confidence level [%]
β_i	Relative fuel cost [€/MWh]
γ	CVaR weighting parameter [-]
η_k	Charging/discharging efficiency [%]
θ	Damping factor [-]
μ_{sc}	Uncertain capacity price multiple [-]
τ	Length of time step [h]

Chapter 1

Introduction

In recent years, the European electricity system has undergone a rapid transition towards a generation mix increasingly dominated by intermittent renewable energy sources such as wind and solar power. While these technologies are essential for achieving European decarbonization targets, their variability, combined with the retirement of conventional generation capacity, has intensified concerns regarding long-term resource adequacy and the ability of energy-only electricity markets to deliver sufficient investment incentives. As a result, European policymakers and regulators have adopted an increasingly supportive stance toward capacity remuneration mechanisms (CRMs), contributing to a growing number of capacity markets across Europe designed to safeguard long-term security of supply. Many of these mechanisms combine yearly contracts with longer-term contracts for new investments, making contract duration an increasingly important design parameter within capacity markets because of its direct influence on investment incentives and the resulting capacity mix.

The effect of contract duration is particularly relevant for emerging flexibility technologies such as industrial demand response. These technologies often face different investment structures compared to conventional generation assets, which can result in them not qualifying for the same long-term contracts granted to generation and storage technologies. As a result, unequal contract durations may unintentionally favor certain technologies over others, thereby influencing the resulting long-term capacity mix. Despite the importance of contract duration design within European capacity markets, limited research has been conducted on how differentiated contract durations affect technology competition and investment outcomes.

This thesis examines the effect of unequal capacity market contract durations on the long-term capacity mix. More specifically, the research evaluates how different contract duration frameworks influence the competitiveness of gas-fired generation, lithium-ion battery storage, and zinc electrolysis demand response represented as a virtual battery resource. To evaluate these effects, this thesis develops an equilibrium model that simulates a capacity market auction. Investors face uncertainty

through a set of energy-only market scenarios derived from a separate economic dispatch model and a set of capacity market price scenarios defined within the capacity market model itself. These uncertainty scenarios are used to model the bidding behavior of risk-averse capacity providers. A Belgian-inspired case study is used to compare multiple policy cases, ranging from strongly asymmetric contract duration frameworks to fully equalized long-term contract eligibility across technologies.

The remainder of this thesis is structured as follows. Chapter 2 situates the topic within the academic literature and the evolving policy perspective surrounding CRMs. It reviews existing capacity market implementations across Europe and internationally, discusses the role of contract durations, and examines current capacity market modeling approaches, thereby identifying the research gap and contribution of this thesis. Chapter 3 first introduces the modeling of the energy-only market through an economic dispatch model, followed by the equilibrium-based capacity market model. It presents the mathematical formulation in a case study-agnostic manner in order to provide a broadly applicable framework for assessing contract duration designs. Chapter 4 presents the case study inspired by the Belgian electricity market and discusses the considered technologies, assumptions, and contract duration cases used to compare the resulting effects through the performance metrics defined at the end of the chapter. Chapter 5 analyzes the model results and evaluates the differences between the cases in terms of capacity prices, investment decisions, producer surplus, and total system costs. Finally, Chapter 6 concludes the thesis by summarizing the main findings and discussing policy implications and directions for future research.

Chapter 2

Capacity markets: background and literature review

This chapter provides an overview of the current state of capacity markets and the relevant academic literature. It first introduces the economic rationale for capacity mechanisms and discusses the main implementation designs currently used in practice. Section 2.2 reviews the European regulatory framework and recent policy developments, followed by an overview of existing capacity markets. Section 2.3 focuses on contract duration as a key design parameter and discusses its theoretical and practical implications. Finally, Section 2.4 reviews the principal modeling approaches used in the literature and assesses how the duration of the contract is treated within existing models, thereby identifying the research gap addressed in this thesis.

2.1 Implementation of capacity remuneration mechanisms

This section discusses how capacity remuneration mechanisms (CRMs) are implemented in practice. It begins by outlining the economic rationale for their introduction in Section 2.1.1 and then reviews the main design options used across different electricity markets in Section 2.1.2, with a more in-depth review of capacity markets and their key design parameters in Section 2.1.3.

2.1.1 Rationale for capacity remuneration mechanisms

The rapid cost reductions in renewable technologies, combined with environmental objectives, have significantly increased the share of renewables in the generation mix [56]. As a result, conventional thermal units are increasingly displaced during hours of high renewable output. This displacement reduces their operating hours and erodes their revenues [55]. Consequently, investment incentives for these conventional units decline, although they remain essential for maintaining adequacy during hours of high residual demand, which occur when electricity demand is high

and renewable generation is low.

This is the case in energy-only markets, where generators recover their fixed and variable costs through revenues earned in short-term electricity markets (day-ahead, intraday, and balancing markets). Investment incentives therefore rely on energy price formation, including scarcity prices. Scarcity periods are time intervals in which available generation and flexibility resources are insufficient to comfortably meet demand, leading to tight system conditions and typically resulting in very high electricity or imbalance prices. In contrast, hybrid market designs supplement energy-only market revenues with policy instruments such as capacity remuneration mechanisms, contracts for difference (CfDs), or other revenue-stabilizing schemes. These instruments introduce additional revenue streams that reduce exposure to short-term price volatility and explicitly aim to address adequacy, decarbonization, or investment risk concerns.

Two main rationales are put forward for the implementation of capacity remuneration mechanisms as an additional investment incentive. First, although energy-only markets are theoretically capable of delivering adequate investment signals, risk-averse investors may be reluctant to commit capital on the basis of a limited number of highly volatile scarcity hours [29]. Furthermore, many energy-only markets impose price caps during scarcity periods [60], [48], [29]. Since 2022, the EU wholesale electricity market has operated under a harmonized maximum clearing price limit. Originally set at a baseline of €3,000/MWh, the system utilizes an automatic upward adjustment mechanism that increases the ceiling when prices repeatedly approach the limit [25]. The baseline has since stabilized at €4,000/MWh. One of the main arguments for maintaining such a price cap is the mitigation of margin call requirements in energy derivatives markets, an issue discussed in greater detail in [1]. Such caps prevent prices from reaching the levels that would otherwise signal scarcity and allow conventional generators to earn the necessary returns [35], [55].¹ The situation in which capacity that is needed for adequacy becomes unprofitable due to suppressed scarcity prices is widely referred to as the missing-money problem in electricity markets.

Second, the absence of an explicit market for reliability results in missing market signals, which creates a missing-market problem, as noted by [29]. In current electricity markets, consumers cannot directly express their willingness to pay (WTP) for different levels of security of supply. As a result, the system lacks a mechanism to reveal the value they place on reliability. In principle, such a signal could arise through demand response prices that reflect consumers' willingness to reduce consumption during scarcity. Another example of a missing market arises because energy-only markets provide no long-term revenue stabilization mechanism, leaving capital-intensive projects exposed to highly uncertain and concentrated price distributions, which can deter investment even in the absence of price caps [44].

¹Reference [35], as cited in [29]

However, as argued in [58], security of supply also exhibits the characteristics of a public good in the absence of complete smart metering: network operators cannot selectively disconnect individual consumers based on their WTP. Since reliability is provided uniformly to all users, regardless of their willingness to accept disconnection, market-based incentives for adequacy remain incomplete. These factors strengthen the case for capacity mechanisms. By creating a dedicated market through which consumers indirectly express the value of reliability, capacity mechanisms help overcome the missing money and the missing market problem and support a more efficient level of capacity provision.²

2.1.2 Approaches to capacity remuneration

A capacity remuneration mechanism is typically established and administered by the transmission system operator (TSO) and the regulatory authority. It incentivizes investment in new capacity by offering capacity providers an additional revenue stream. This section discusses the main approaches and design options used to implement capacity remuneration. First, capacity payments represent the simplest form of a capacity mechanism, consisting of administratively determined payments made by a public authority to generators based on their installed or available capacity, with the payment level potentially varying according to technology type, availability criteria, and total installed capacity [29]. This system risks being less economically efficient than other types of CRMs. Current examples include Portugal, Spain and South Korea [43].

Another, straightforward response to security of supply concerns is the introduction of a strategic reserve. Under this model, the system operator procures a predefined volume of capacity outside of the regular electricity market to guarantee additional backup during scarcity events. The procured units are not allowed to participate in the wholesale electricity market and placed under the full operational control of the system operator, who decides when to dispatch them. In principle, strategic reserves are intended to be activated only as a last resort and at clearly defined scarcity price thresholds, ensuring that their deployment does not distort market outcomes. In practice, however, transmission system operators can activate these reserves at levels below the theoretical scarcity threshold. Such premature activation risks suppressing scarcity prices in the energy-only market and crowding out market-based investment signals. This is a central criticism in the literature, as highlighted by [8], since the interference can undermine competitive adequacy solutions and weaken incentives for private investment in capacity. Current examples of strategic reserves include Germany and Sweden [29].

A third option for addressing adequacy concerns is the introduction of a decentralized capacity market via a supplier capacity obligation. Since 2017, France has

²Reference [58], as cited in [29]

operated such a decentralized capacity market rather than a centralized capacity auction [29]. Under this system, electricity suppliers (retailers) are required to hold capacity certificates corresponding to their expected peak demand, including an additional reliability margin. These certificates are issued to generation units, demand response providers, and storage facilities that are certified by the TSO based on their expected availability during peak periods, typically demonstrated through historical performance. As a result, the French system does not rely on a centrally determined procurement volume or a single market clearing price, distinguishing it from most other capacity market designs.

A final option for addressing adequacy concerns is the introduction of a centralized capacity market. In this model, the system operator establishes a dedicated market for reliability and acts as the single buyer of capacity. The operator specifies a reliability target and conducts annual or multi-year auctions. As part of the market design, the responsible authority must choose between two principal contractual frameworks: centralized capacity market with or without a reliability option [29].

A centralized capacity market design entails that capacity providers receive a fixed remuneration in exchange for committing to provide a specified volume of capacity during scarcity events, as signaled by the system operator [29]. These capacity payments are independent of actual energy production and are earned as long as the resource remains available. If a provider fails to deliver the committed capacity when called upon, it is subject to financial penalties. These penalties both compensate for the lost capacity and reinforce the incentive to fulfill contractual obligations. They are determined by the system operator and are proportional to the magnitude of the capacity shortfall. In many designs, penalty schemes are symmetric and capped, allowing over-performance to offset under-performance while limiting total financial exposure and thereby avoiding excessive risk for market participants. Another option is to assign the obligation to procure capacity not to the system operator, but to large load-serving entities, such as retailers or major consumers [39]. Under this framework, these entities are required to purchase sufficient capacity from generators to cover their expected demand³. This approach is commonly referred to as a capacity obligation system and is used in several U.S. capacity markets (New York, PJM, MISO, and New England).

In addition, a capacity market may adopt a reliability option framework. In this design, the system operator procures financial call options on wholesale electricity prices from capacity providers. Each option is defined by a strike price set at, or close to, scarcity price levels. When the wholesale electricity price during a scarcity event exceeds the strike price, the capacity provider is required to pay back the difference between the market price and the strike price. This mechanism effectively protects consumers from extreme price spikes, while forcing generators to remain available during scarcity periods. It stabilizes generator revenues by replacing volatile scarcity

³Unlike a decentralized capacity market, this design relies on a centrally administered auction.

earnings with a fixed premium, while simultaneously protecting consumers from extreme price spikes through an effective price cap at the strike price. [39] argues that this design represents a more cost-efficient implementation of a capacity market.

At a high level, a centralized capacity market is conceptually equivalent to a decentralized capacity obligation scheme in which the system operator acts as the aggregate of all consumers and therefore as the single buyer. In both designs, capacity providers commit to making a specified volume of capacity available during scarcity periods in exchange for a capacity payment. This commitment is referred to as a capacity obligation in [38]. It is important to note, however, that terminology in the literature is not always used consistently. The term capacity obligation is sometimes used to describe a decentralized capacity market framework [29]. For clarity, this thesis adopts the following terminology. A *centralized capacity market* refers to a mechanism without a reliability option framework. A *reliability option* refers to a capacity market that incorporates financial call options with a predefined strike price. The term *capacity obligation* is used exclusively to denote the commitment by capacity providers to deliver availability during scarcity periods.

2.1.3 Key design parameters in capacity markets

The performance of a capacity market ultimately depends on its core design parameters, which critically determine its efficiency and long-term adequacy outcomes. Beyond the choice of contractual form, a capacity market must determine the volume of capacity to be procured for each delivery year. This volume is typically established through a demand curve constructed by the system operator on the basis of a resource adequacy assessment. Such assessments rely on reliability metrics including the Loss of Load Expectation (LOLE) and the Expected Energy Not Served (EENS). These metrics are used to derive a downward-sloping demand curve, allowing the auction to jointly determine both the clearing price and the quantity of capacity procured for a given year. [36] provides a comparative analysis of distinctive capacity market demand curve designs, examining price-inelastic, elastic, and semi-elastic specifications in order to approximate the optimal demand curve.

Capacity procurement is conducted with different lead times [15]. In most capacity markets, the majority of capacity is procured several years ahead of delivery, commonly around four years in advance, with additional adjustment auctions held closer to delivery, such as one or two years ahead. It is often assumed that different auction lead times favor different capacity technologies. As a result, the technology mix of submitted bids may vary across lead times. However, there is currently little evidence to support this assumption. An examination of recent auctions in the Belgian capacity market does not reveal a clear trend. In the Y-1 auction for delivery year 2026 [13], the Y-2 auction for delivery year 2027 [14], and the Y-4 auction for delivery year 2027 [12], both gas-fired power plants and large-scale battery storage participated in comparable volumes across the different lead times. Demand-side management shows a slight indication of being more prevalent in shorter lead-time

auctions. One important difference related to auction lead times can be observed. Y-1 auctions are almost exclusively composed of existing capacity providers. In contrast, Y-4 auctions include a substantial share of newly built capacity. In the Y-4 auction for delivery year 2027, new capacity accounted for 23% of the total contracted volume [12]. This reflects the fact that new capacity investments generally require sufficient development time for permitting, financing, and construction before becoming operational. While project-specific lead times exceeding the standard Y-4 horizon may be granted in exceptional circumstances, such as construction delays or particularly complex projects, these cases remain the exceptions [15].

Next, the system operator must define the rules that determine when a scarcity period is declared. A scarcity period is the time interval during which capacity providers are required to deliver the volume of capacity they committed to in the capacity market auction. In most designs, scarcity periods are not defined by a threshold in wholesale electricity prices. Instead, they are triggered by a predefined positive imbalance price threshold, which is established prior to the auction [15].

Finally, capacity markets may employ either a pay-as-clear (e.g. Italy [57]) or a pay-as-bid auction format (e.g. Belgium [15]), which are discussed further in Section 3.3. In addition, capacity markets define technology-specific derating factors for capacity providers, which are explained further in Section 4.2.

2.2 Evolution of capacity markets in the EU

This section reviews the evolution of the European regulatory framework governing capacity mechanisms and situates current capacity markets within that policy context. Section 2.2.1 outlines the previous EU approach under Regulation (EU) 2019/943, in which capacity mechanisms were treated as temporary and exceptional instruments. Section 2.2.2 then discusses the recent changes introduced by the 2024 Electricity Market Reform, which consider capacity mechanisms as potential structural elements of electricity market design. Finally, Section 2.2.3 provides an overview of existing capacity market implementations in selected countries, highlighting key design characteristics and emerging policy developments.

2.2.1 Previous EU policy framework on capacity mechanisms

Under the regulatory framework established by EU Regulation 2019/943 [51], European policy treated capacity mechanisms as exceptional instruments rather than a standard feature of electricity market design. Member states were only permitted to introduce capacity mechanisms after demonstrating that all other relevant market failures had been addressed. These failures included, among others, the presence of price caps and barriers to demand response participation. Capacity mechanisms were therefore positioned as a measure of last resort.

Article 20 of EU Regulation 2019/943 specified that capacity mechanisms could

only be considered where security of supply concerns were structural in nature, rather than the result of temporary or short-term imbalances. This evaluation had to be supported by both a national adequacy assessment and a European Resource Adequacy Assessment conducted by ENTSO-E, ensuring a consistent and coordinated evaluation across member states.

If a structural adequacy problem was identified, member states were expected to first assess the suitability of a strategic reserve, which was regarded as less distortive to market functioning than a market-wide capacity mechanism. Only if it could be demonstrated that a strategic reserve would be insufficient to address the adequacy issue, was a member state allowed to introduce a capacity market. Even then, capacity markets were required to be temporary in nature, with their continued necessity subject to regular reassessment. In addition, the regulation imposed strict design requirements. Capacity mechanisms had to be technology neutral, allow for cross-border participation, and comply with an emissions performance standard of 550 gCO₂eq/kWh. Furthermore, procurement volumes were limited to the minimum necessary to address the identified adequacy concern.

2.2.2 Recent developments under the Electricity Market Reform

This policy stance has been significantly revised following the adoption of the Electricity Market Reform in April 2024 [24]. In this reform, the European Union explicitly acknowledged that, in the transition towards a carbon-neutral power system, capacity mechanisms may evolve into a structural element of electricity market design rather than remaining temporary interventions. As stated in the accompanying press release, capacity mechanisms *“will become a more structural element of the electricity market and will no longer be temporary measures”*.

The reform also altered the hierarchy between different types of capacity mechanisms. Strategic reserves are no longer required to be assessed as the default first option, and market-wide capacity markets are now explicitly recognized as legitimate structural capacity mechanisms alongside strategic reserves. Nevertheless, the technical design requirements and reporting obligations remain in place, and member states must continue to demonstrate that the implemented capacity mechanisms effectively address identified adequacy concerns.

In the report published by the European Commission as part of the Electricity Market Design reform [24], the Commission recommends streamlining approval procedures for capacity mechanisms, including simplifications related to reliability standards and the use of European Resource Adequacy Assessments (EERAs). This evolving policy perspective is mirrored in the academic debate. Whereas the long-run efficiency of energy-only markets and the necessity of capacity remuneration mechanisms were highly controversial until a few years ago, a growing body of literature now supports hybrid market designs that complement energy-only markets with long-term instruments [44]. The common argument is that electricity markets

are structurally incomplete and fail to provide sufficient investment signals for capacity adequacy. Reflecting this broader shift in both policy and scholarship, several member states have intensified their efforts to develop capacity market frameworks. In particular, both Spain [27] and Germany [6] have initiated formal processes to implement capacity markets, as discussed in the next section.

2.2.3 Overview of existing capacity market implementations

Table 2.1 provides an overview of existing capacity market implementations. These are based in the European Union, reflecting the EU’s electricity market framework, as well as the North-East of the United States, which represents some of the earliest adopters of capacity markets. The table reports the contract durations applied in each capacity market. The implications of these variations are examined in Section 2.3.

The earliest capacity markets were implemented in the United States. ISO-PJM [53], ISO New England [34], and ISO New York [28] introduced centralized capacity markets between 2007 and 2010. These markets rely exclusively on one-year contract durations. In Europe, Great Britain [46] launched the first capacity market in 2014. The British design combines one-year contracts for eligible technologies, with longer-term contracts for specific new investments that meet predefined eligibility criteria, most often gas-fired power plants. Since then, several additional European capacity markets have been introduced, including Ireland [10], Poland [54], Italy [57], and Belgium [15] alongside the special case of France as discussed in Section 2.1.2. With the exception of France, European capacity markets all apply a combination of short-term and longer-term contract durations. Outside Europe and the United States, Japan introduced a capacity market in 2024. The reliability option framework is a more recent development within capacity markets. Ireland was the first European country to implement this design in 2018, followed by Italy, Japan, and Belgium.

Following the adoption of the Electricity Market Reform in 2024, which explicitly moved away from viewing capacity mechanisms as measures of last resort, there has been renewed interest in the introduction of capacity markets across several major European electricity systems. In parallel with this broader policy shift, Spain had already taken a definitive decision in 2023 to establish a market-wide centralized capacity mechanism [27]. The first capacity auctions are expected to take place in 2026, following the approval of the final legal framework. Germany constitutes another important case, although it is currently at an earlier stage of reform. The country has signaled its intention to transition from its existing strategic reserve system towards a hybrid capacity mechanism that combines elements of a strategic reserve with capacity market procurement [6]. While the precise design and regulatory details are still under discussion, initial implementation steps are expected around 2027 or 2028.

TABLE 2.1: Overview of active capacity markets in 2026, ordered by first delivery year.

Country	Implementation	Contract Length	Start
PJM	Centralized CM	1 year contracts	2007
New England	Centralized CM	1 year contracts	2010
New York	Centralized CM	1 year contracts	2010
Great Britain	Centralized CM	1-year main auction, specific contracts up to 10 years	2014
France	Decentralized CM	1 year obligation	2017
Ireland	Reliability option	1-year main auction, specific contracts up to 10 years	2018
Poland	Centralized CM	1-year main auction, specific contracts up to 15 years	2021
Italy	Reliability option	1-year main auction, specific contracts up to 15 years	2022
Japan	Reliability option	1 to 20 years	2024
Belgium	Reliability option	1-year main auction, specific contracts up to 15 years	2025
Spain	Centralized CM	Under consideration	2027

2.3 Contract duration in capacity markets

An important design parameter of capacity markets concerns the treatment of contract duration. Section 2.3.1 first discusses the current implementation of different contract durations in existing capacity markets, before outlining the advantages and disadvantages of long-term versus short-term contracts. Section 2.3.2 subsequently examines the eligibility criteria commonly applied to long-term contracts and their potential implications for the resulting capacity technology mix.

2.3.1 Long-term contracts: rationale and trade-offs

As shown in Table 2.1, most existing implementations combine short-term contracts, typically of one year, with longer-term contracts offered to newly built capacity. By providing a stable and predictable stream of capacity payments, long-term contracts lower investment risk, improve financing conditions, and consequently reduce the cost of capital. Moody’s Investor Service has noted that capacity revenue and the revenue predictability it entails leads to a higher credit rating, resulting in a lower cost of debt [2]. As a result, they can increase the number of capacity-providing units that are financially viable, thereby enhancing overall system reliability. Evidence from medium- to long-term (1-20-year) contracting in electricity markets supports

this effect, as shown by [47]. As a result, such contracts can therefore contribute to an improvement in security of supply.

At the same time, longer contract durations involve trade-offs. They reduce the flexibility of the transmission system operator in future procurement rounds, as a portion of capacity is locked in for multiple years [45]. Subsequently, they can also limit the operational and strategic flexibility of the generation units subscribing to them, as future operational decisions and market participation become constrained by long-term availability obligations. Moreover, long-term contracts effectively transfer investment risk from private investors to the system operator and, ultimately, to consumers. These arrangements can be interpreted as a form of indirect subsidy ⁴.

Relevant literature on this issue includes the analysis in [3], which studies contract duration within a reliability options framework. The authors show that longer capacity contracts embed a higher option value because they reduce investors' exposure to electricity prices and policy uncertainty. This risk reduction increases the value of the contract to providers and raises expected procurement costs for the central buyer. Within a real-options framework, they conclude that procuring capacity through multiple shorter-duration contracts generally leads to lower expected total capacity costs.

Contract duration should therefore balance investor risk mitigation against potential distortions in technology competition, particularly given that different technologies require varying levels of revenue certainty. The current literature offers little evidence on how longer contracts, potentially acting as an indirect subsidy, influence the resulting capacity mix.

2.3.2 Eligibility criteria for long-term contracts

In capacity markets, such as those in the United Kingdom [46] and Belgium [15], all new capacity investments are in principle eligible for longer-term contracts, provided they comply with strict eligibility criteria. These criteria favor investments in gas-fired power plants and storage units. One key requirement concerns the capital expenditure of the project, as eligibility depends on meeting a minimum CAPEX threshold per MW. Another important condition is that the additional capacity must commit to being constant and available over a long period. For demand response (DR) capacity, meeting these requirements is often challenging. DR resources can often be aggregated portfolios of smaller capacity providing units, which makes it difficult to satisfy minimum investment thresholds or to guarantee long-term constant availability. Moreover, investments in DR frequently take the form of increased flexibility or efficiency improvements rather than an increase in installed capacity. The Belgian electricity market regulator CREG explicitly states: "*investments to increase flexibility or efficiency or to reduce emissions without increasing installed*

⁴World Trade Organization: *a subsidy shall be deemed to exist if: there is any form of income or price support* [61]

capacity: are not the goal of CRM (can be financed by successive one-year contracts)" [5]. As a result, demand response is effectively excluded from multi-year capacity contracts, confining it to one-year contracts. This design effectively restricts access to long-term risk mitigation to a limited set of technologies.

Near the completion of this thesis in April 2026, CREG published a report [9] at the request of the Belgian Ministry of Energy assessing the conditions under which industrial demand response DR could contribute more strongly to adequacy through the capacity market. A central focus of the report is the possibility of making investments in industrial DR eligible for long-term contracts. The report states that long-term contracts are intended to support large investments in clearly measurable *added capacity*. The current Belgian framework is defended on the basis that investments in industrial DR are often multifunctional. According to the regulator, these investments are generally aimed at improving industrial flexibility, production reliability, energy efficiency, or carbon efficiency, rather than solely increasing deployable electricity capacity. As a result, certain industrial investments that contribute to flexibility and adequacy may not fully satisfy the criteria currently applied for awarding multi-year contracts. At the same time, the report acknowledges that industrial DR investments can require similarly high upfront investments and long payback periods as gas-fired power plants and battery storage, both of which are currently eligible for long-term contracts. The Belgian TSO therefore expressed openness toward evaluating longer contract durations for specific industrial DR investments on a case-by-case basis. The report also justifies the Belgian framework by comparing it with other European capacity markets, where long-term contracts for demand response may exist but are generally subject to strict eligibility requirements. In addition, concerns are raised regarding potential distortions of competition in industrial sectors producing goods. However, one may argue that this concern is of limited relevance, as the primary objective of the capacity market is to secure adequacy in the most economically efficient manner, while participation remains open to all.

Because of this difference in eligibility, extending contract durations may reduce technological diversity within capacity markets and increase the carbon intensity of the capacity mix. This concern is especially relevant given that gas-fired generation has a carbon intensity on average between 400 and 500 gCO₂eq/kWh [59], placing it close to the emissions performance limit of 550 gCO₂eq/kWh established under EU Regulation [24]. A particularly consequential example of this effect is the Polish capacity market which predates the EU CM carbon intensity rule [40]. As a result of long-term contracts, a large portion of capacity procured on the basis of coal power plants is still in contract to this day, possibly being one of the reasons for Poland's comparatively slow progress in phasing out coal.

2.4 Modeling approaches and research gap

The literature employs several distinct modeling approaches to analyze capacity markets, each emphasizing different aspects of market design and investment behavior. Section 2.4.1 summarizes an early overview of these approaches provided in [29], which distinguishes four broad categories of models. Each framework captures different dimensions of capacity markets and involves trade-offs between realism, complexity, and tractability. However, the existing modeling literature does not explicitly account for differences in contract duration, and therefore provides limited insight into how contract length may affect the resulting capacity mix, as will be examined in Section 2.4.2.

2.4.1 Modeling approaches for capacity markets

The first category consists of system dynamics models. These models represent capacity markets through aggregated investment flows and feedback loops, with a focus on long-term adequacy and investment cycles. System dynamics models are well suited for analyzing multi-year dynamics and structural trends. However, they do not account for competitive bidding behavior, technological characteristics, and detailed auction design. As a result, their applicability is limited in settings where market outcomes are strongly influenced by strategic choices or high shares of renewable energy sources.

A second category is agent-based modeling. Agent-based models explicitly represent diverse market participants with differing technical characteristics and economic objectives, who make investment and bidding decisions, even under imperfect information. Capacity mechanisms are introduced as rules that affect agents' revenue streams and investment incentives, allowing for the analysis of strategic behavior, learning, and adaptation over time. The main limitation of this approach lies in its high computational burden, as the optimization problems of multiple agents must be solved sequentially. This often restricts the temporal scope or operational detail of the analysis. A recent application of agent-based modeling is provided by [58], which compares the effectiveness of different capacity remuneration mechanisms with a particular focus on weather uncertainty. The authors adopt an agent-based approach because it allows the representation of markets with lumpy investment decisions and imperfect foresight.

Third, optimization models incorporate capacity markets into a centralized cost-minimization framework, typically by adding constraints or additional revenue terms. These models offer a high level of operational detail and are well suited for analyzing dispatch, system costs, and adequacy under different policy scenarios. However, they generally assume perfect competition and therefore cannot capture strategic bidding behavior or market power in capacity auctions. As a consequence, the resulting auction prices and investment decisions are determined by system-wide cost optimization rather than by strategic interactions between market participants. In

addition, these models can typically represent relatively simple capacity remuneration mechanisms, such as centralized markets with uniform pricing, but are less suited to modeling more complex designs such as reliability option frameworks.

Finally, equilibrium models are commonly chosen when the focus lies on the interaction between individual decision-making and market outcomes in liberalized electricity markets. In these models, capacity auction outcomes result from the simultaneous profit-maximizing behavior of individual agents. Compared to agent-based models, equilibrium models typically generate static equilibrium outcomes rather than dynamic trajectories over time. To maintain computational tractability, they often rely on simplified representations of operational constraints and network structures. A recent application of equilibrium modeling is presented in [37]. The study incorporates capacity markets into a long-run equilibrium generation expansion planning model, with a focus on the risk aversion of market participants. Risk aversion is explicitly represented through the inclusion of a conditional value-at-risk (CVaR) in the agents' objective functions, allowing the model to capture trade-offs between expected returns and downside risk. Since an equilibrium model is used in this thesis, a schematic visualization from [29] is provided for illustration in Figure 2.1.

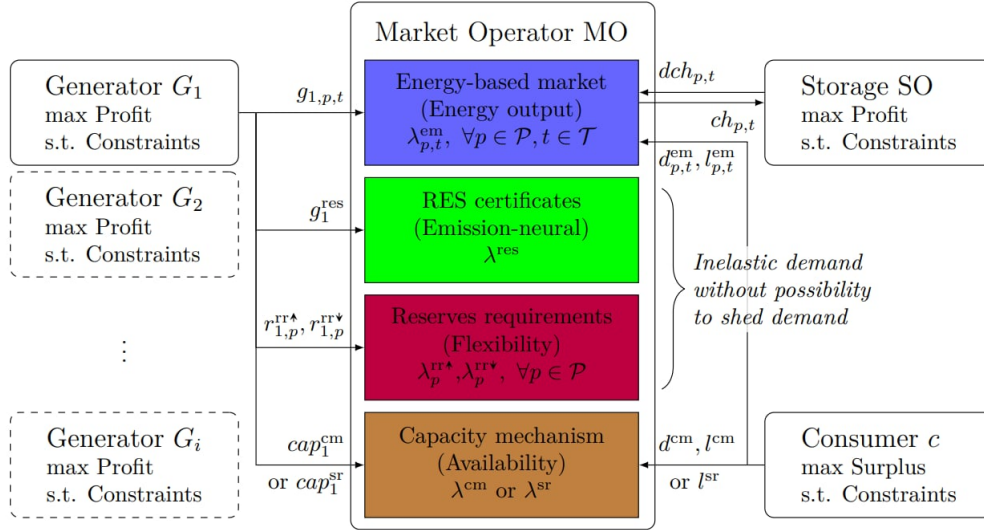


FIGURE 2.1: Schematic overview of an equilibrium model for a capacity market, adapted from [29].

2.4.2 Research gap and contribution

In the current literature, the effect of contract duration on capacity market bidding behavior and auction outcomes receives very limited attention. This is notable given that most capacity markets employ a mixed procurement structure (see Table 2.1), combining long-term contracts for newly built gas-fired power plants and storage units (dominated by gas-fired power plants) with annual auctions for other capacity providers.

The rationale behind the indirect subsidy via long-term contracts, only holds if the eligible technologies are absolutely necessary to ensure security of supply. Otherwise, if alternative technologies would succeed in capacity auctions under identical contract durations, technology-specific long-term contracting risks distorting competition. In that case, the capacity market, and by extension the overall electricity market, may become less economically efficient.

Three studies come close to evaluating this issue: [29], [3], and [45]. First, [29] provides an overview of existing modeling approaches for different types of capacity remuneration mechanisms, with particular attention given to how CRM design affects market outcomes under investor risk aversion. However, the framework does not explicitly model auction behavior and instead represents capacity mechanisms through adequacy constraints and capacity payments. In addition, capacity revenues are assumed to be riskless, and contract durations are identical for all agents.

Second, [3] qualitatively examines the effects of capacity contract duration on investment, bidding behavior, and welfare under seasonal load and generation patterns. However, the analysis focuses on contract durations within a single year and therefore does not consider multi-year capacity contracts. In addition, the framework does not model different auction outcomes.

Third, and most closely related to the issue addressed in this thesis, [45] applies financial option theory to value capacity bids from the provider's perspective, modeling capacity obligations as a European put option, i.e. a contract that gives its holder the right to sell at a predetermined price on a specified future date. The study evaluates how capacity market design parameters, including contract duration, influence bidding behavior. However, the option value in the model is primarily driven by the opportunity cost of forced operation at low wholesale electricity prices, which is less relevant since high imbalance prices, defining the scarcity periods, are strongly correlated with high wholesale electricity prices [4]. In addition, the analysis does not consider new capacity investment and focuses on the perspective of a single CCGT agent. Finally, the option valuation is based on risk-neutral assumptions, rather than risk-averse.

The preceding discussion highlights a clear research gap regarding the effects of contract duration in capacity markets, particularly how different contract durations

influence investment decisions across technologies in a setting with risk-averse market participants. This thesis contributes to the literature by analyzing how variations in contract duration affect investment in new capacity and the resulting long-term capacity mix. In particular, it evaluates whether long-term contracts with specific eligibility criteria, as observed in current capacity market designs, create an unequal playing field between different capacity-providing technologies. To address this question, the thesis employs an equilibrium modeling framework in which agents face uncertainty in wholesale electricity profits and capacity market revenues and exhibit risk-averse behavior. Within this framework, a simplified capacity market is simulated over a long-term horizon. The aim is to assess how alternative contract duration designs influence investment decisions and the resulting capacity mix.

Chapter 3

Model formulation

This section describes the modeling approach used to analyze the research gap. Section 3.1 provides an overview of the core modeling framework, including the main inputs, data flows, and expected outputs. The methodology is based on the combination and interaction between two sequential models. Specifically, we first leverage an economic dispatch model to estimate the profits of capacity providers in wholesale electricity markets, which is described in more detail in Section 3.2. These profits then serve as input to a bespoke equilibrium model that represents the capacity market and determines investment in new capacity, as discussed further in Section 3.3. The chapter focuses on the model formulation without assigning specific parameter values or data inputs. The concrete implementation is presented in Chapter 4.

3.1 General modeling framework

This section provides a high-level overview of the core modeling approach and the interaction between the two models, as illustrated in Figure 3.1. The guiding logic is to model the capacity market within an equilibrium model that simulates risk-averse capacity providers over a long-term horizon (e.g. 15 years). An equilibrium modeling approach is adopted because capacity market auction outcomes emerge from the individual optimization and bidding behavior of market participants, rather than from a centralized optimization of the overall electricity system. Within this framework, uncertainty is not uniform across all market participants. While all capacity providers face uncertainty in their energy-only market revenues, those that are not eligible for long-term capacity contracts are additionally exposed to uncertainty in future capacity prices. This results in a higher overall revenue uncertainty for these agents.

Future adequacy requirements are expected to exceed the currently available capacity, creating a need for new investment in capacity-providing technologies. The equilibrium model simulates these investment decisions over a long-term horizon and determines the future technology mix. By varying contract durations and the

associated exposure to revenue uncertainty across technologies, the model can be used to assess their impact on investment outcomes and the resulting capacity mix. For example, cases may restrict certain technologies, such as gas-fired plants, from accessing long-term contracts, or allow demand response technologies to participate in them, enabling the model to evaluate how contract duration affects investment decisions and addresses the central research question of this thesis.

Investment decisions are based on the evaluation of combined energy-only market (EOM) and capacity market profits. The model therefore requires reliable input representing uncertainty in future EOM profits. This is achieved using an economic dispatch model, which simulates a full future reference year of electricity generation for a set of EOM scenarios based on uncertain parameters such as gas prices, carbon prices, electricity demand, and renewable generation capacity. An economic dispatch model is formulated as an optimization problem for short-term market clearing, as risk aversion and strategic bidding behavior play a more limited role in short-term operational decisions, allowing the market outcome to be approximated through centralized cost minimization.

The result of this model is a set of EOM scenarios $s \in S$, each providing the expected profits for every generator relative to its installed capacity. The scenarios representing uncertainty in future capacity payments are defined as $sc \in SC$. The equilibrium model, which simulates the capacity market auction, incorporates both types of scenarios to determine the expected profits and associated risk premiums.

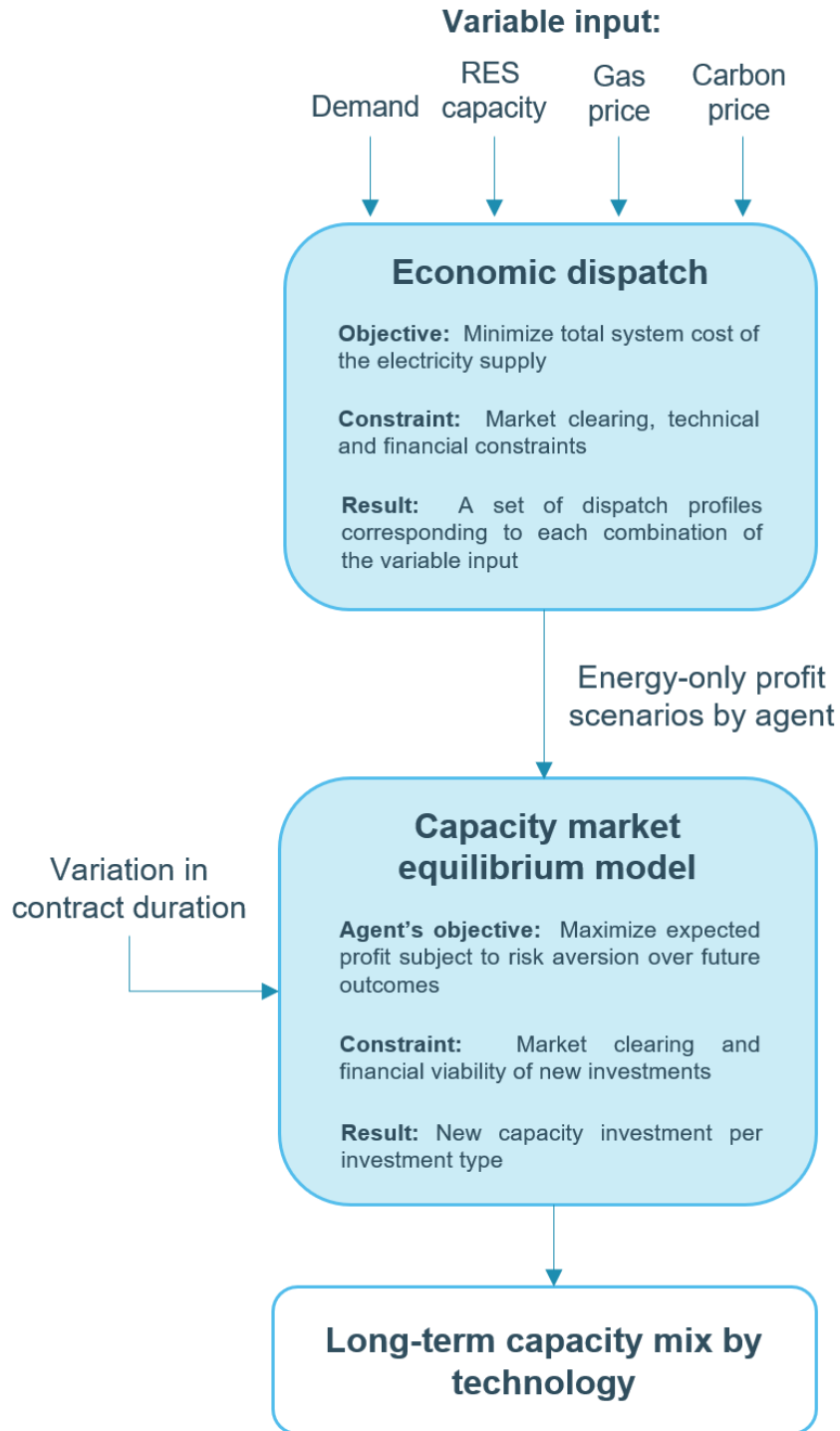


FIGURE 3.1: Core model idea overview.

3.2 Economic dispatch model

This section describes the economic dispatch model used to generate a set $s \in S$ of energy-only profit scenarios to take into account as input in the equilibrium model. An economic dispatch model is an optimization model that determines the units' generation schedules such that total system operating costs are minimized, while satisfying demand and respecting technical constraints. It is used to estimate the EOM profits of capacity providers by modeling how electricity is dispatched in wholesale markets. This approach has been selected because it provides a realistic and computationally efficient representation of the short-term market clearing. The generation schedules, prices, and resulting profits are consistently estimated under operational constraints for all resulting scenarios. The sets are introduced first, followed by the formulation of the objective function and model constraints.

Sets of considered units

The economic dispatch is performed over time steps $j \in J$ for all participating units. These units are categorized into generating units $i \in I$ and storage units $k \in K$, as illustrated in Figure 3.2. The rationale for modeling demand response as a storage unit is further elaborated in Section 4.1.

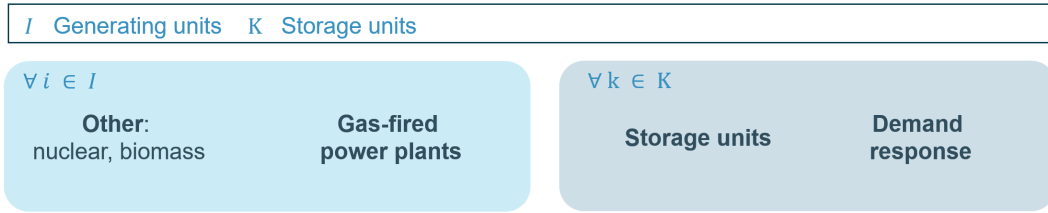


FIGURE 3.2: Technology sets used in the economic dispatch model.

Objective

The objective of the model is to minimize the total variable cost of meeting electricity demand in each time step $j \in J$ of (fixed) duration (τ). The total variable cost consists of fuel costs ($gcd_{i,j}$), emission-related costs ($ccd_{i,j}$), and costs associated with unserved energy (ens_j).

$$\text{Min.} \quad \sum_{i \in I, j \in J} \tau \cdot gcd_{i,j} + \sum_{i \in I, j \in J} \tau \cdot ccd_{i,j} + \tau \cdot VOLL \cdot ens_j \quad (3.1)$$

The fuel cost of generator i at timestep j is determined by multiplying a (fixed) variable unit cost (β_i) with the production volume ($g_{i,j}$). This variable unit cost is determined by the primary fuel cost corrected by the plants efficiency, with an additional variable operation and maintenance cost ($O\&M_i$) added.

$$gcd_{i,j} = \beta_i \cdot g_{i,j} \quad \forall i \in I, j \in J \quad (3.2)$$

The emission-related cost of generator i at timestep j is calculated as a function of the EU ETS carbon price (α) and the carbon intensity parameter (CI_i) associated with each generator. The carbon intensity parameter is a technology-specific parameter that depends on the carbon intensity of the primary fuel and the unit's efficiency.

$$ccd_{i,j} = \alpha \cdot CI_i \cdot g_{i,j} \quad \forall i \in I, j \in J \quad (3.3)$$

Market clearing

The main economic constraint of the model imposes that, for each time step, total system generation ($\sum_{i \in I} g_{i,j}$), including storage discharge ($\sum_{k \in K} d_{k,j}$), must equal total residual demand ($ResD_j$), including storage charging ($\sum_{k \in K} c_{k,j}$). Residual demand is defined as total electricity demand net of renewable generation. The demand balance includes a correction term to account for energy-not-served (ens_j). The inequality sign reflects that if residual demand becomes sufficiently negative such that the right-hand side of the constraint is negative, it becomes non-binding, as the model assumes renewable energy sources curtail generation in this scenario.

$$\sum_{i \in I} g_{i,j} + \sum_{k \in K} d_{k,j} \geq ResD_j + \sum_{k \in K} c_{k,j} - ens_j \quad \forall j \in J \quad (3.4)$$

Generation and demand constraints

Energy-not-served must be positive and cannot exceed residual demand. Generation must be positive and cannot exceed the plant's capacity.

$$0 \leq ens_j \leq ResD_j \quad \forall j \in J \quad (3.5)$$

$$0 \leq g_{i,j} \leq cap_i \quad \forall i \in I, j \in J \quad (3.6)$$

Storage constraints

The energy level of storage units ($e_{k,j}$) is determined by charging ($c_{k,j}$), discharging ($d_{k,j}$), and the storage efficiency (η_k). The stored energy as well as the charging and discharging power, is constrained by their respective maximum capacities (E_k, P_k). A cyclic boundary is set for the energy state of the storage units.

$$e_{k,j} - e_{k,j-1} = \tau \cdot \eta_k \cdot c_{k,j-1} - \tau \cdot \frac{d_{k,j-1}}{\eta_k} \quad \forall k \in K, j \in J \setminus \{0, end\} \quad (3.7)$$

$$e_{k,end} = e_{k,0} \quad \forall k \in K \quad (3.8)$$

$$0 \leq e_{k,j} \leq E_k \quad \forall k \in K, j \in J \quad (3.9)$$

$$0 \leq c_{k,j} \leq P_k \quad \forall k \in K, j \in J \quad (3.10)$$

$$0 \leq d_{k,j} \leq P_k \quad \forall k \in K, j \in J \quad (3.11)$$

Post-processing

Following optimization, the market price p_j in each time step is derived as the shadow price of the market clearing constraint (Equation 3.4), divided by the duration of the time step τ .

The generator operational profit is then computed in post-processing as the difference between market revenues and operational costs. For simplicity, this will be referred to as profit. For each generator, profit is accumulated over all time steps in which the unit is dispatched, as the product of generation and market price minus fuel and emission costs. For storage units, profit is computed as the revenue from discharging minus the cost of charging, both valued at the prevailing market price. Formally:

$$\Pi_i = \tau \cdot \sum_{j \in J} g_{i,j} \cdot (p_j - O\&M_i) - fcd_{i,j} - ccd_{i,j} \quad \forall i \in I \quad (3.12)$$

$$\Pi_k = \tau \cdot \sum_{j \in J} d_{k,j} \cdot p_j - c_{k,j} \cdot p_j \quad \forall k \in K \quad (3.13)$$

This model is evaluated under multiple scenarios based on variations in key parameters, specifically the carbon price (α), gas price (affecting β_i), and renewable generation capacity scenarios (affecting $ResD_j$). For each scenario, the operational profit is calculated, resulting in a set of energy-only market scenarios $s \in S$ with associated profits for each generating unit.

3.3 Capacity market model

To analyze bidding behavior and market outcomes in a capacity market, this section presents an equilibrium model that determines the investment decisions of market participants. Rather than optimizing from the perspective of a single agent, the model represents a market-clearing mechanism in which each participant submits a bid equal to their minimum required capacity remuneration, i.e. their (risk-adjusted) break-even bid price. The regulator then selects the least-cost combination of technologies that satisfies the capacity target. The market is assumed to clear under a pay-as-cleared design, which under standard assumptions is theoretically equivalent to a pay-as-bid mechanism, as bidders base their bids on the expected clearing price [7]. First, Section 3.3.1 defines the categorization of technologies into the applied sets and their corresponding uncertainty timelines. Section 3.3.2 describes the different profit components determining the bid price of each technology, including the incorporation of risk aversion. Finally, Section 3.3.3 explains the implementation of the equilibrium model using the Big-M method.

3.3.1 Uncertainty representation and technology categorization

This section describes how technologies are categorized based on their exposure to revenue uncertainty. A key feature of the model is the endogenous treatment of

risk. Investors are assumed to be risk-averse and face uncertainty regarding future profits. Energy-only market uncertainty is represented through a set of scenarios derived from the economic dispatch model. The capacity market auction itself is only explicitly cleared for the first year of the modeled horizon. Capacity providers eligible for long-term contracts receive this initially cleared capacity price over the full capacity market horizon considered in the model (e.g. a 15-year contract) and therefore only face uncertainty in energy-only market profits. In contrast, non-eligible providers only receive the initially cleared capacity price for the first year. For the remaining years, future capacity prices are represented through a set of optimistic and pessimistic capacity price scenarios $sc \in SC$, defined as multiples of the initially cleared capacity price. As a result, non-eligible providers are exposed to both energy-only market uncertainty and future capacity market uncertainty. The additional uncertainty is reflected in their bidding behavior through a higher risk premium.

The uncertainty timeline of the capacity market is illustrated in Figure 3.3. Year $j = 0$ represents the year in which the capacity auction is cleared. At this stage, agents make their investment decision through their bid under uncertainty and therefore know the auction outcome once selected, for example scenario sc_3 in the figure. For all subsequent years, uncertainty in capacity market revenues is represented through a set of scenarios $sc \in SC$, which remain identical across the remaining years of the modeled horizon. Energy-only market uncertainty is modeled similarly, with the distinction that for the EOM, the outcome in year $j = 0$ is also uncertain.

Sets of considered technologies

In addition to the categorization of the economic dispatch agents, all capacity providers participating in the capacity market $p \in P$ are further divided into those eligible for long-term contracts $e \in E$ and those not eligible $ne \in NE$, as illustrated in Figure 3.4. Note that when the model is used to evaluate different contract duration designs, the categorization changes across cases. For example, some cases may allow demand response providers to become eligible for long-term contracts, while in other cases all technologies may become ineligible. The illustrated categorization represents the current setup and is therefore treated as the base case.

3. MODEL FORMULATION

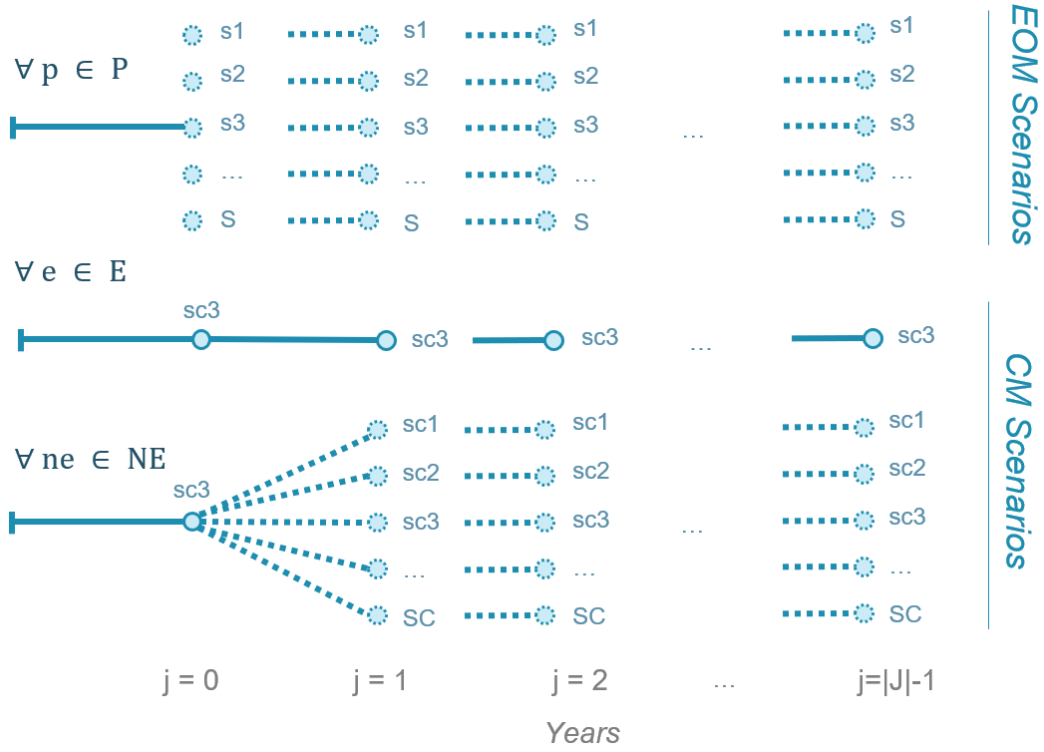


FIGURE 3.3: Illustration of the EOM and CM uncertainty timelines for eligible and non-eligible capacity providers, with sc_3 representing an example auction outcome.

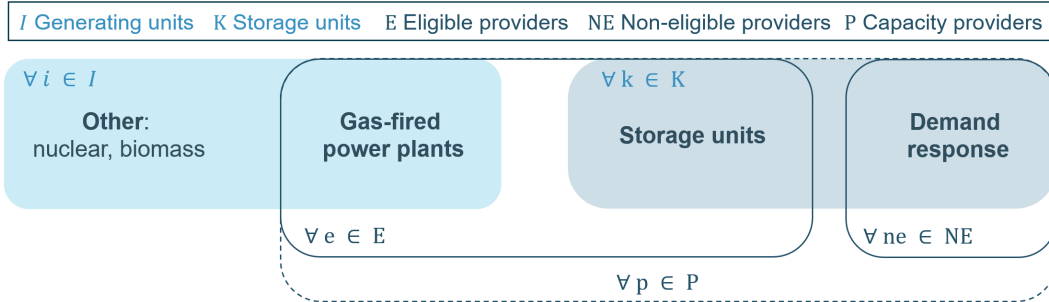


FIGURE 3.4: Agent sets used in the equilibrium model.

3.3.2 Capacity price formation

This section first defines the market-clearing condition, which determines the investment volume (x_p) required to meet the capacity target. It subsequently defines the profit function associated with the capacity investment for each technology. The

profit function is then extended with a risk aversion term and an energy-only market adjustment term, which captures the reduction in EOM profits a technology experiences as additional capacity of that technology is installed. Finally, the resulting profit definition is transformed into a technology-specific bid function based on a (risk-adjusted) break-even condition.

Market clearing

The demand curve set by the regulator to clear the capacity auction is simplified to a volume constraint (i.e. perfectly inelastic demand). The sum of existing capacity (y_p) and newly built capacity (x_p), both adjusted by technology-specific derating factors (F_p), must be sufficient to meet the target capacity volume to be procured (CT). In the remainder of the model, existing capacity is not explicitly modeled in the bidding process, as its capacity bid is assumed to be zero.¹

$$\sum_{p \in P} y_p \cdot F_p + \sum_{p \in P} x_p \cdot F_p = CT \quad (3.14)$$

Expected profits

The relative profit for all capacity providing technologies $p \in P$ is based on the following formulation:

$$profit_p = \sum_{j \in J} \frac{F_p \cdot \lambda \cdot x_p}{(1 + r_p)^j} + \sum_{j \in J} \frac{\sum_{s \in S} P_s \cdot EM_{p,s}}{(1 + r_p)^j} \cdot x_p - IC_p \cdot x_p \quad \forall p \in P \quad (3.15)$$

The first term represents the profit obtained from the capacity market, determined by the cleared capacity price (λ). The second term captures the expected future profits from the energy-only market. Relative EOM operational profit (EM : Energy-only Margin) is defined as the total operational profit (Π_i) divided by installed capacity, expressed in €/MW. This metric forms the primary input from the economic dispatch model into the capacity market model, as it represents the expected per-MW EOM profit of each technology. The expected EOM profit is calculated as the probability-weighted sum of the scenario-specific profits $EM_{p,s}$, where all scenario probabilities P_s are assumed equal. These future profits are subsequently discounted using a technology-specific discount rate r_p . Finally, the investment cost is incorporated as a one-time upfront expenditure.

Capacity technologies that are not eligible for long-term contracts face uncertainty in future capacity prices, as they must participate in repeated annual auctions. The uncertainty is modeled through a set of capacity price scenarios $sc \in SC$, where each scenario is represented by a multiplier μ_{sc} applied to the capacity price cleared

¹This reflects the assumption that capacity payments constitute an additional revenue stream for existing units without requiring additional costs (i.e. investment costs are considered sunk, such that their capacity bids can be zero, provided they do not incur losses in the EOM).

in $j = 0$. This leads to the following profit formulation for non-eligible plants:

$$\begin{aligned} profit_{ne} = & F_{ne} \cdot \lambda \cdot x_{ne} + \sum_{j \in J \setminus \{0\}} \frac{F_{ne} \cdot x_{ne} \sum_{sc \in SC} P_{sc} \cdot \mu_{sc} \cdot \lambda}{(1 + r_{ne})^j} \\ & + \sum_{j \in J} \frac{\sum_{s \in S} P_s \cdot EM_{ne,s}}{(1 + r_{ne})^j} \cdot x_{ne} - IC_{ne} \cdot x_{ne} \quad \forall ne \in NE \end{aligned} \quad (3.16)$$

Risk aversion

To incorporate risk aversion into the previous risk-neutral formulation, this thesis applies a Conditional Value-at-Risk (CVaR) approach. The objective is to define profits as expected profits minus a weighted risk measure. More specifically, the expected profit is adjusted by subtracting a weighted CVaR term ($-\gamma \cdot CVaR_p$), where the parameter γ represents the degree of risk aversion. A higher value of γ implies that investors assign greater importance to unfavorable outcomes relative to expected returns. The CVaR approach assigns greater weight to low profit (or loss) scenarios by focusing on the tail of the profit distribution. A confidence level $1-\beta$ defines which percentage of scenarios is considered non-critical (e.g. $\beta = 0.1$ corresponds to the worst 10% of scenarios). The CVaR is then calculated as the average relative profit (or loss) over this subset of worst-case scenarios. A more detailed description of this methodology can be found in [29].

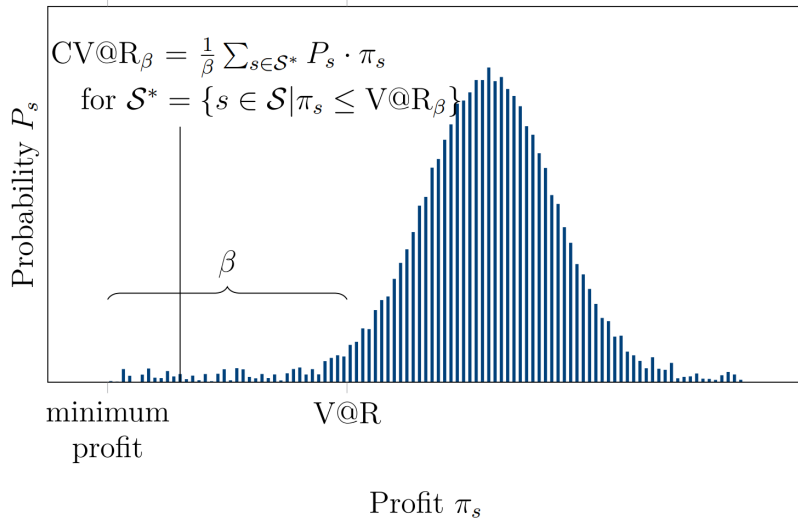


FIGURE 3.5: Visualization of conditional value-at-risk, as discussed in [29].

The CVaR formulation for energy-only market uncertainty is defined as follows:

$$\overline{EM}_e = \frac{\sum_{s \in S} EM_{e,s}}{|S|} \quad \forall e \in E \quad (3.17)$$

$$tail_e = \{EM_{e,s} \mid EM_{e,s} \leq EM_{e,(\lceil \beta \cdot |S| \rceil)}\} \quad \forall e \in E \quad (3.18)$$

$$CVaR_e = \frac{1}{|tail_e|} \sum_{s \in tail_e} \overline{EM}_e - EM_{e,s} \quad \forall e \in E \quad (3.19)$$

The formulation above applies to eligible technologies, as they only account for uncertainty in EOM profits. Non-eligible technologies additionally face uncertainty in future capacity market revenues. Their risk is therefore calculated over the combined set of EOM scenarios and capacity market scenarios, based on the worst combinations of an energy-only market scenario and a capacity market scenario. A variable CE_{ne} (combined earnings) is introduced:

$$CE_{ne,s,sc} = EM_{ne,s} + F_{ne} \cdot \lambda \cdot \mu_{sc} \quad \forall ne \in NE \quad (3.20)$$

$$tail_{ne} = \{CE_{s,sc} \mid CE_{s,sc} \leq CE_{\lceil \beta \cdot |S| \cdot |SC| \rceil}\} \quad \forall ne \in NE \quad (3.21)$$

$$CVaR_{ne} = \frac{1}{|tail_{ne}|} \sum_{s \in tail_{ne}} \overline{EM}_{ne} + F_{ne} \cdot \lambda \cdot \mu_{avg} - CE_{ne,s,sc} \quad \forall ne \in NE \quad (3.22)$$

Chapter 5 also evaluates intermediate cases in which non-eligible technologies receive a contract duration (CD) longer than one year, but shorter than the full long-term contract horizon of 15 years ($|J|$). In these cases, the calculation of $CE_{ne,s,sc}$ must be adjusted, as the combined earnings are now a combination of certain and uncertain capacity prices:

$$CE_{ne,s,sc} = EM_{ne,s} + \frac{CD}{|J|} \cdot F_{ne} \cdot \lambda + \frac{|J| - CD}{|J|} \cdot F_{ne} \cdot \lambda \cdot \mu_{sc} \quad \forall ne \in NE \quad (3.23)$$

The remainder of the model formulation remains unchanged.

The CVaR term is then subtracted from expected profits, scaled by a weighting parameter γ :

$$\sum_{s \in S} P_s \cdot EM_{p,s} - \gamma \cdot CVaR_p \quad \forall p \in P \quad (3.24)$$

With this implementation, a circular dependence arises because risk-adjusted profits depend on the cleared capacity price λ , while the cleared capacity price itself is determined by the model results and therefore depends on the risk-adjusted profits. As a result, the model must be solved iteratively. The iterative procedure starts from a reference capacity price λ_{ref} . After each iteration, the obtained cleared capacity price is used to update λ_{ref} until the difference between the cleared capacity price and λ_{ref} is smaller than €1/MW. To avoid oscillations in the model, damping is implemented, with a damping factor ($\theta \in [0, 1]$):

$$\lambda_{ref,new} = \lambda_{cleared} \cdot \theta + (1 - \theta) \cdot \lambda_{ref,previous} \quad (3.25)$$

Energy-only investment adjustment

The current soft-linking approach between the economic dispatch model and the equilibrium model implicitly assumes that newly built capacity does not affect future EOM profits. However, in reality, additional investment in a given technology reduces the profitability of that same technology by increasing market competition and changing price formation in the electricity market. For example, a large increase in battery capacity would reduce the profitability of battery storage itself, as batteries increasingly compete for the same price spreads and thereby erode each other's arbitrage opportunities. To account for this effect, the model includes an energy-only investment adjustment term, which captures the reduction in expected EOM profits as more capacity of a given technology is installed.

The adjustment is modeled as a linear function per agent type $CPC_p \cdot x_{type(p)}$ (with $x_{type(p)} = \sum_{p \in P, type(p)=t} x_p$), estimated using a least squares regression based on data points defined in Section 4.2. As a result, the profitability of a given technology decreases as more capacity of that type is installed.

$$EM'_p = \sum_{s \in S} P_s \cdot EM_{p,s} - CPC_p \cdot x_{type(p)} \quad \forall p \in P \quad (3.26)$$

As this thesis only considers investments in the cheapest or most efficient representative of each technology type, $x_{type(p)}$ is simplified to x_p .

Bid formulation

By rewriting Equation 3.15 and incorporating the risk aversion and energy-only market adjustment terms, the following overall zero-profit condition is obtained:

$$\begin{aligned} profit_e = & \sum_{j \in J} \frac{\sum_{s \in S} P_s \cdot EM_{e,s} - CPC_e \cdot x_e - \gamma \cdot CVaR_e}{(1 + r_e)^j} \cdot x_e \\ & + \sum_{j \in J} \frac{F_e \cdot \lambda}{(1 + r_e)^j} \cdot x_e - IC_e \cdot x_e = 0 \quad \forall e \in E \end{aligned} \quad (3.27)$$

$$\begin{aligned} profit_{ne} = & \sum_{j \in J} \frac{\sum_{s \in S} P_s \cdot EM_{ne,s} - CPC_{ne} \cdot x_{ne} - \gamma \cdot CVaR_{ne}}{(1 + r_{ne})^j} \cdot x_{ne} + \lambda \cdot F_{ne} \cdot x_{ne} \\ & + \sum_{j \in J \setminus \{0\}} \frac{F_{ne} \sum_{sc \in SC} P_{sc} \cdot \mu_{sc} \cdot \lambda}{(1 + r_{ne})^j} \cdot x_{ne} - IC_{ne} \cdot x_{ne} = 0 \quad \forall ne \in NE \end{aligned} \quad (3.28)$$

From these zero-profit conditions, the relative bid price (€/MW) can be derived. Note that in the implemented model, the average value of μ_{sc} is equal to 1, making the capacity revenue term equivalent in both formulations. This results in the

following bid price formulation for eligible and non-eligible technologies:

$$b_p = \frac{IC_p - \sum_{j \in J} \frac{\sum_{s \in S} P_s \cdot EM_{p,s} - CPC_p \cdot x_p - \gamma \cdot CVaR_p}{(1+r_p)^j}}{\sum_{j \in J} \frac{F_p}{(1+r_p)^j}} \quad \forall p \in P \quad (3.29)$$

3.3.3 Equilibrium implementation using the Big-M method

The Big-M method is used to implement the equilibrium model by converting non-linear complementarity conditions into a mixed-integer linear problem that can be solved by standard solvers such as Gurobi. Equations 3.30-3.32 ensure that if a capacity technology is selected ($\delta_p = 1$), the capacity price λ is equal to its bid price. If a capacity technology is not selected ($\delta_p = 0$), the capacity price λ must be less than its bid price.

$$\lambda \geq b_p + M_{big} \cdot (1 - \delta_p) \quad (3.30)$$

$$\lambda \leq b_p + M_{big} \cdot (1 - \delta_p) \quad (3.31)$$

$$\lambda \leq b_p + M_{big} \cdot \delta_p \quad (3.32)$$

Chapter 4

Study design

This section specifies the agents and input data required to implement the model developed in Chapter 3 for a case study based on the Belgian electricity and capacity market. The objective of this case implementation is primarily to obtain qualitative insights and order-of-magnitude effects regarding contract duration design, rather than to provide an exact quantitative forecast of future market outcomes. Specifically, Section 4.1 describes the Belgian wholesale electricity market landscape, which mainly provides the input data for the economic dispatch model. Section 4.2 defines the capacity market participants. Next, Section 4.3 presents the case setups used to evaluate the effect of contract duration on the electricity system. Finally, Section 4.4 defines the performance metrics used in the economic evaluation of the cases.

4.1 The Belgian electricity market

Most of the data used for the economic dispatch model is obtained from the open-source data platform of Elia, the Belgian TSO. Since the capacity market model simulates a 15-year horizon, the year 2033 is used as a representative average year. As a result, several input data series are based on current data that is adjusted to reflect expected conditions in 2033. These adjustments are based on Elia’s *Adequacy and Flexibility Study for Belgium 2026–2036* [17], which provides detailed projections for the Belgian electricity mix over the coming decade. First, the central scenario is discussed in Section 4.1.1. Subsequently, Section 4.1.2 describes how uncertainty is introduced through varying key parameters, namely gas prices, carbon prices, and renewable generation capacity.

4.1.1 Central scenario

The central scenario includes several key input parameters. The gas price is assumed to be $\text{€}30/\text{MWh}_{th}$, which is slightly below the average European TTF gas price over the past five years (excluding crisis periods), but close to the IEA forecast of $\text{€}29.19/\text{MWh}_{th}$ [32], and more conservative than optimistic projections such as [52], which estimates $\text{€}23.54/\text{MWh}_{th}$. The carbon price is set at $\text{€}110/\text{tonCO}_2eq$,

which is higher than current levels (approximately €70–€90 in 2026). However, [50] reports forecasts for 2030 ranging between €80 and €160/tonCO₂eq, placing the chosen value within a plausible range.

Residual demand profile

The residual demand profile is derived from Elia’s measured total load on the Belgian grid [18], from which measured wind generation [21] and photovoltaic generation [20] are subtracted. The data has a quarter-hourly resolution and covers the period from November 1, 2024, to October 31, 2025, as shown in Table 4.1. This period corresponds to the most recent complete capacity market delivery year at the time of writing this thesis.

TABLE 4.1: Total load and renewable production in MW.

Time step	Total load	PV production	Wind production	Residual demand
01/11/2024 00:00	8341	0	295	8046
01/11/2024 00:15	8258	0	336	7923
01/11/2024 00:30	8022	0	338	7684
...	...	...	...	...
31/10/2025 23:45	8394	0	3852	4542

The three scenarios defined in Elia’s adequacy report [17] project an average electricity demand of 118 TWh in 2033, compared to 84.1 TWh in the current data set. This results in an adjustment factor of 1.404¹, which is applied to the total load in Table 4.1. Similar adjustment factors are applied to renewable generation. Based on the projected increase in installed renewable capacity reported in the same study, scaling factors of 1.575 and 2.076 are applied to photovoltaic and wind generation, respectively.

Generators

An estimate of the Belgian installed generation capacity by type is constructed based on an aggregation of sources [19], [17], and [11]. Gas-fired power plants are estimated to account for approximately 10 GW of installed capacity, depending on the scenario assumptions and the technologies included. In this thesis, these are subdivided into 4 GW of modern high-efficiency combined-cycle gas turbines (CCGTs), 2.5 GW of older lower-efficiency CCGTs, 2 GW of open-cycle gas turbines (OCGTs), and 1.5 GW of combined heat and power plants (CHPs). In addition, Belgium is assumed to retain two nuclear reactors with a combined capacity of 2.077 GW. Biomass generation is estimated to account for an additional 0.5 GW of installed capacity.

¹This assumes that the future demand profile scales proportionally without changing shape.

The fuel cost component of the variable cost of gas-fired power plants is determined by the gas price and plant efficiency according to $\frac{p_{gas}}{\eta_i}$. Using a base gas price of €30/MWh_{th} and the efficiencies listed in Table 4.2, obtained from [33], the corresponding fuel costs in the central scenario are calculated and reported in the same table. The carbon intensity values are based on data from [30, 33], a more detailed explanation of the variable cost parameters is provided in Appendix A. Due to its role in price setting and profit formation, gas-fired power plants are assigned an additional operation and maintenance (O&M) cost of €10/MWh.

Fuel cost estimates for the base-load plants are derived from [33] and [31]. An approximation of 15 €/MWh is used for nuclear power and 60 €/MWh for biomass power plants. The carbon intensity of both technologies is assumed to be negligible and is therefore set to zero.

Given this generation mix, the current setup may lead to unrealistically high prices during periods of high demand. Since the model does not account for imports during scarcity periods, nor for demand-side price elasticity, it tends to overestimate electricity prices in high-demand situations. This consequently overestimates the profits generators can obtain in the energy-only market and therefore also affects their bids in the capacity market. As a stylized correction, a simplified form of price elasticity is introduced through four types of demand response. These are modeled as generators with increasing variable costs: €100/MWh with a capacity of 500 MW, €200/MWh with a capacity of 1000 MW, €250/MWh with a capacity of 500 MW, and €300/MWh for the final DR type. The last DR category is assumed to have unlimited capacity, effectively setting the maximum price level in the model, which will later be referred to as the scarcity price. This prevents the model from reaching the value of lost load (*VOLL*), which lead to frequent and unrealistically high price spikes in scenarios characterized by high demand and low renewable generation.

TABLE 4.2: Generating units in the economic dispatch model.

Plant (type)	Capacity (MW)	Fuel cost (€/MW)	Carbon intensity (tonCO ₂ eq/MWh _e)	η_i (%)
Modern CCGT (Gas)	4000	48.39	0.326	62
Old CCGT (Gas)	2500	57.69	0.388	52
OCGT (Gas)	2000	75.00	0.505	40
CHP (Gas)	1500	68.18	0.3	44
Nuclear (Base)	2077	15.00	0	-
Biomass (Base)	500	60.00	0	-
Low (DR)	500	100.00	0	-
Medium (DR)	1000	200.00	0	-
High (DR)	500	250.00	0	-

Storage

Currently, the main form of electricity storage in Belgium is pumped hydro storage, accounting for approximately 1 GW of power capacity and 5.6 GWh of energy capacity [17]. However, due to technical and economic constraints, as well as participation in balancing and frequency reserve markets that are beyond the scope of this model, these facilities often operate significantly below their maximum storage and discharge capacities [11]. To approximate this behavior, a simplified pumped hydro storage unit with an energy capacity of 1 GWh and a power capacity of 0.5 GW is included in the model. A charging and discharging efficiency of 87% is assumed, based on the reported round-trip efficiency of 75% for Belgian pumped hydro storage facilities reported by Engie [22].

A relatively recent form of electricity storage in the Belgian market is large-scale lithium-ion battery energy storage systems (BESS). Based on [17] and [11], the installed battery capacity in Belgium in 2025 is estimated at approximately 600 MW. Note that the installed battery capacity is fixed at the 2025 level, as additional battery investments in future years are endogenously modeled in the equilibrium framework as newly built capacity. For simplicity, all battery systems are assumed to have a storage duration of three hours, meaning that the energy capacity is approximated as three times the installed power capacity. These battery systems are assumed to have a charging and discharging efficiency of 96% (roundtrip efficiency 92.2%) [42].

Demand response

There are many possible technologies and industrial processes that can provide demand response capacity. This thesis specifically considers investment in the demand response capabilities of a zinc production plant. The electrolysis stage of zinc production is highly suitable for demand response through load shifting. The production process is very electricity intensive and can be ramped up or down quickly without significantly affecting the end product. This type of industrial process is present in the Belgian electricity market through the zinc production facilities of Nyrstar, as discussed in [41]. The concept of adjusting electricity consumption around a reference production level while maintaining a constant industrial output is often described as a virtual battery [49]. An investment in this type of capacity can be interpreted as an upgrade of industrial infrastructure. By oversizing industrial capacity, the facility gains additional operational flexibility, allowing it to provide more capacity to the electricity system and participate more actively in the capacity market.

In the economic dispatch model, this type of demand response is represented as a battery with an efficiency of $\eta = 100\%$ and an energy volume equal to six times its power capacity. The six-hour duration reflects the assumption that zinc electrolysis can shift electricity consumption over several consecutive hours without significantly

affecting total production output, while still remaining constrained by operational continuity and process limitations.²

4.1.2 Scenario variations

The different economic dispatch scenarios are based on uncertainty in gas prices, carbon prices, total electricity demand, and installed wind and photovoltaic capacity. Three gas price scenarios are considered: the base case shown in Table 4.2, a low-price case with a 25% decrease to €22.5/MWh_{th}, and a high-price case with a 25% increase to €37.5/MWh_{th}. The carbon price is represented through a low-price scenario of €80/tonCO₂eq and a high-price scenario of €140/tonCO₂eq, compared to the central scenario assumption of €110/tonCO₂eq. Both values fall within the range of long-term EU ETS forecasts reported in [50]. Electricity demand uncertainty is represented through low- and high-electrification scenarios, in which electricity demand equals 90% and 110% of the base case demand, respectively. These adjustment factors are applied to the residual demand profile shown in Table 4.1. Finally, optimistic and conservative adjustment factors of 1.15 and 0.85 are applied to the installed capacities of wind and photovoltaic generation in the residual demand calculation. The cross-combination of these scenario variations generates 48 scenarios, which, together with the central scenario without demand, wind, or solar factors, result in a total of 49 economic dispatch scenarios, all assumed to have equal probability.

TABLE 4.3: Datapoint variations in economic dispatch scenarios.

Gas price	€22.5/MWh _{th}	€30/MWh _{th}	€37.5/MWh _{th}
Carbon price	€80/tonCO ₂ eq		€140/tonCO ₂ eq
Demand factor	0.9		1.1
Wind factor	0.85		1.15
Solar factor	0.85		1.15

4.2 Capacity market agents

In the capacity market model, the auction is cleared to determine the most competitive outcome for meeting the capacity target. The total procured capacity volume is set at 13 500 MW, compared to the currently procured volume of around 7.2 GW [13]. This value is considerably higher, as electricity demand is expected to increase (see the demand adjustment in Section 4.1.1) while Elia’s adequacy reports project that up to 20% of existing gas-fired capacity may exit the market by 2033. After subtracting the existing capacity y_p already included in the economic dispatch

²A limited storage duration is additionally assumed because industrial demand response facilities may simultaneously participate in balancing and ancillary service markets, reducing the flexibility that can be fully allocated to the day-ahead market.

model, the resulting net new capacity investment requirement over the 15-year horizon equals 4 358 MW. Note that this value represents required derated capacity (MW_d) rather than the total nominal installed capacity (MW_n) to be invested.

All generation (besides the DR Low, Medium and High) and storage technologies included in the economic dispatch model are eligible to participate as capacity providers in the equilibrium model. However, due to the structure of the auction model, participation of new capacity investments is limited to the lowest-cost technologies within each category (e.g. newly built power plants are assumed to be highly efficient units). Specifically, three new technologies can participate in the capacity market: modern CCGT plants representing gas-fired power plants, lithium-ion battery energy storage systems (BESS) representing storage, and zinc electrolysis demand response representing DR. Base-load generators do not participate in the capacity market, consistent with the Belgian CM framework. Nuclear power is excluded because the need for the Belgian CM, as approved by the European Commission [23], was originally justified on the basis of the Belgian nuclear phase-out, which was estimated to create a need for 3.9 GW of new capacity by 2032. In general, capacities participating in the CM cannot simultaneously receive other forms of governmental support or subsidies. This effectively excludes existing renewable generation and biomass capacity, which are already supported through Contracts for Difference (CfDs) or other support mechanisms.

Investment cost

The investment cost (IC_p) of a newly built modern CCGT plant in Belgium is assumed to be €900 000/ MW_n , aligned with the overnight investment cost reported in [33]. Investment cost estimates for lithium-ion battery energy storage systems vary widely, and have been decreasing rapidly in recent years. An overnight investment cost of €500 000/ MW_n is assumed, representing a more optimistic estimate compared to the 2020 values reported in [33]. Finally, the investment cost of zinc electrolysis demand response capacity is difficult to estimate, as it is unclear which share of the investment should be attributed to zinc production and which part to capacity provision. An assumed cost of €1 500 000/ MW_n is used. This relatively high value is chosen because the objective is to evaluate the effect of contract duration on demand response technologies, such as virtual batteries, that remain relatively expensive compared to conventional generation and storage technologies. All capacity technologies are assigned a discount rate of 6%. The purpose of this assumption is to avoid accounting for investment risk twice, as risk is already explicitly represented through the CVaR term in the model.

Capacity derating factor

In capacity markets, a derating factor represents the share of its installed capacity that a provider is allowed to offer in the market based on its expected availability during scarcity situations. It is implemented to account for differences in reliability and

availability between technologies, ensuring that intermittent or energy-constrained technologies contribute less to adequacy targets than fully dispatchable capacity. The capacity derating factor of gas-fired power plants is set at 90%. In practice, the derating factors applied in the Belgian capacity market differ between providers [12] and are determined by Elia through detailed adequacy assessments [16]. For reference, modern CCGT providers have received derating factors of up to 91%. The derating factor for zinc production demand response is set at 100%, as its ability to provide capacity is assumed to be primarily constrained by physical zinc storage space. Since such storage infrastructure is relatively inexpensive compared to conventional electricity storage technologies, zinc DR is assumed to provide very long-duration flexibility with near-full availability during scarcity situations.

For battery energy storage systems, the derating factor generally depends on the storage duration. Longer-duration storage technologies generally receive higher derating factors because they are able to sustain discharge over extended scarcity periods and therefore contribute more reliably to resource adequacy. This highlights the importance of duration in adequacy assessments, particularly for short-duration battery storage technologies [26]. To represent this effect endogenously and consistently, the derating factor of lithium-ion BESS in this model is calculated from the output of the economic dispatch model as shown below. More specifically, the availability of the storage unit during scarcity periods, in our model defined as time steps with prices equal to €300/MWh, is computed as the production during scarcity events relative to the nominal discharging power (Eq. 4.1). This results in an effective derating factor of 37% for the modeled BESS technology.

$$F_k = \text{mean}\left(\frac{g_{k,j}}{P_k}\right) \quad j \in J_{\text{scarcity}} \quad (4.1)$$

TABLE 4.4: Overview of the investment costs and derating factors of CM technologies.

Technology	Overnight IC (€/MW _n)	Annualized IC (€/MW _n /yr)	Derating factor (%)
Modern CCGT	900 000	87 420	90
Lithium-ion BESS	500 000	48 567	37
Zinc DR	1 500 000	145 700	100

Investment adjustment for energy-only market profits

As described in Section 3.3 and defined in Equation 3.26, a linear factor is used to adjust the energy-only profits of each capacity provider based on the installed capacity of its technology type. This factor is approximated through a linear regression using eleven data points obtained by running the central scenario of the

economic dispatch (s_0) for different installed capacity levels ($cap_{i,t} = cap_{i,t-1} + 400$ MW). This analysis is performed separately for each technology, after which the resulting EOM operational profits are regressed as a function of installed capacity. The resulting capacity profit curves (CPC_i) are estimated at €34M/GW² for modern CCGT plants, €8M/GW² for BESS, and €19M/GW² for zinc demand response. The data points and their corresponding linear regressions are shown in Figure 4.1. Although the BESS and zinc DR technologies exhibit a slightly concave relationship between installed capacity and EOM operational profits, the regression errors remain sufficiently small to justify the use of a linear approximation for simplicity. This simplification implies that the model slightly overestimates EOM operational profits for modest additional investments in BESS and zinc DR capacity.

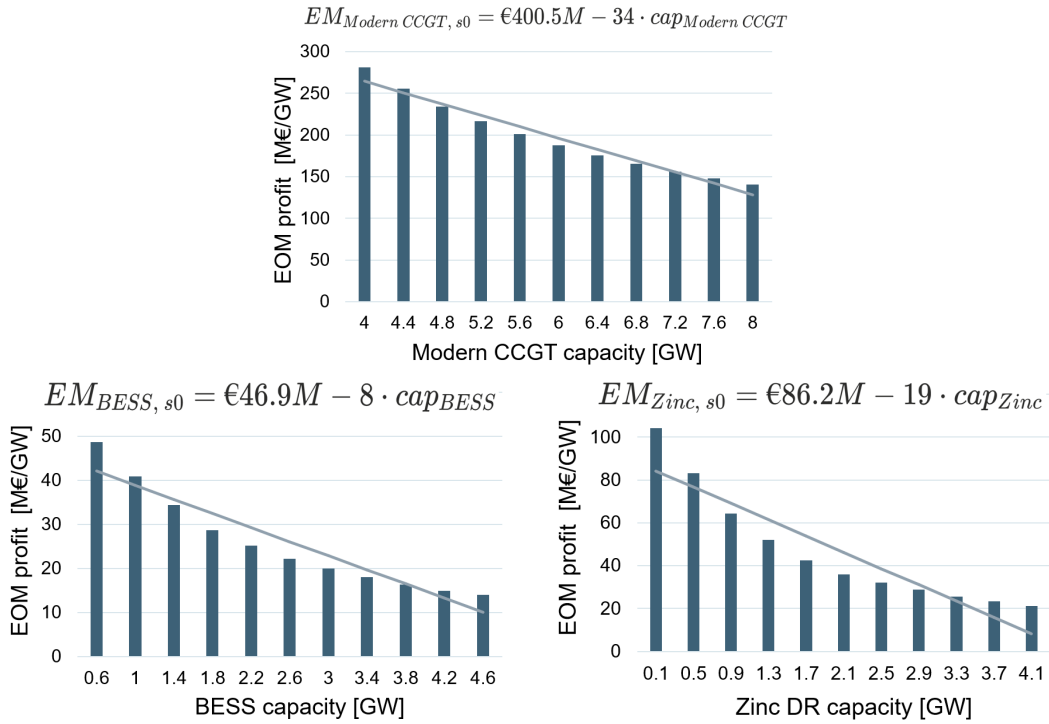


FIGURE 4.1: Relative EOM profit as a function of capacity for Modern CCGT (top), BESS (bottom left), and zinc DR (bottom right), based on economic dispatch measurements (bars) and linear regression approximations (line).

Risk aversion

The degree of risk aversion in the model is determined by the CVaR weighting parameter γ and the confidence level $1 - \beta$. The confidence level defines which percentage of scenarios is considered non-critical, while the remaining worst-case scenarios are included in the CVaR calculation. The following risk term is subtracted

from the expected risk-neutral profits:

$$-\gamma \cdot CVaR_p(\beta) \quad (4.2)$$

The CVaR weighting parameter is set to $\gamma = 0.5$, while the confidence level is set to 80% or $\beta = 0.2$. In practice, this means that 50% of the average loss compared to the mean in the worst 20% of scenarios is subtracted from the expected profits. A sensitivity analysis of the results with respect to these parameters is presented in Section 5.5.

Capacity market uncertainty

The capacity price uncertainty is modeled through a multiplier μ_{sc} applied to the effective capacity price, as described in Section 3.3. The multipliers range from a 100% decrease to a 100% increase relative to the cleared capacity price in the initial auction at $j = 0$. This wide range reflects the strong sensitivity of capacity prices to changes in key model parameters, as will be illustrated through the sensitivity analyses in the next chapter. All capacity price scenarios are assumed to have equal probability.

$$\mu_{sc} = 0.1 \cdot sc \quad \forall sc \in \{0, \dots, 20\} \quad (4.3)$$

4.3 Contract duration case configurations

The capacity market cases are defined based on different contract duration setups. An overview of the corresponding case setups and the numbering used throughout the remainder of this thesis are shown in Figure 4.2. As discussed in the literature review, gas-fired power plants and battery energy storage systems are typically the only technologies eligible for long-term contracts. In the current Belgian design, newly built investments in these technologies can receive contracts of up to 15 years, while demand response providers generally only qualify for one-year contracts, including in cases where new assets or infrastructure investments are required. This setup is referred to as the current design (case 1). To evaluate the effect of contract duration on auction outcomes and the resulting long-term generation mix, two additional benchmark cases are considered. In the first benchmark case, referred to as case 0, no technology receives long-term contracts and all providers participate only through one-year contracts. In the second benchmark case, referred to as case 15, all newly built capacity technologies, including demand response, are eligible for 15-year contracts. In addition, several intermediate cases are evaluated in which demand response technologies receive contract durations between 1 and 15 years, while the eligibility of the other technologies for 15-year contracts remains unchanged. These cases are referred to as the demand response compromise cases.

4.4 Performance metrics

To evaluate the economic implications of the different cases, three metrics are calculated for each case $c \in C$: producer surplus (PS_c), cost to consumers (CTC_c),

	Gas	BESS	Zinc
CASE 0	1 Y	1 Y	1 Y
CASE 1	15 Y	15 Y	1 Y
⋮			
CASE X	15 Y	15 Y	X Y
⋮			
CASE 15	15 Y	15 Y	15 Y

FIGURE 4.2: Overview of cases with varying contract durations.

and the resulting societal cost (SC_c). These values are determined after incorporating the auction-cleared capacity investments into the economic dispatch model and averaging over all EOM scenarios $s \in S$. Total EOM revenues ($R_{EOM,c}$) are calculated as the electricity price multiplied by the sum of total generation and storage discharge. Total EOM cost ($C_{EOM,c}$) are calculated as the variable production cost ($gcd_{i,j} + ccd_{i,j}$) multiplied by generation, plus the cost associated with storage charging. Total CM revenue ($R_{CM,c}$) is calculated as the cleared capacity price (λ) multiplied by the total procured derated capacity volume.

$$R_{EOM,c} = \sum_{s \in S} \frac{1}{|S|} \sum_{j \in J} p_j \cdot \tau \cdot \left(\sum_{i \in I} g_{i,j} + \sum_{k \in K} d_{k,j} \right) \quad \forall c \in C \quad (4.4)$$

$$C_{EOM,c} = \sum_{s \in S} \frac{1}{|S|} \sum_{j \in J} \tau \cdot \left(\sum_{i \in I} g_{i,j} \cdot (gcd_{i,j} + ccd_{i,j}) + \sum_{k \in K} p_j \cdot c_{k,j} \right) \quad \forall c \in C \quad (4.5)$$

$$R_{CM,c} = \lambda \cdot \sum_{p \in P} F_p \cdot y_p + F_p \cdot x_p \quad \forall c \in C \quad (4.6)$$

Finally, producer surplus is calculated by subtracting the annualized investment costs of the newly built capacity investments together with their associated risk premiums:

$$PS_c = R_{EOM,c} - C_{EOM,c} + R_{CM,c} - \sum_{p \in P} \frac{IC_p}{\sum_{j \in J} \frac{1}{(1+r_p)^j}} \cdot x_p - \sum_{p \in P} \gamma \cdot CVaR_p \cdot x_p \quad \forall c \in C \quad (4.7)$$

The cost to consumers is equal to total producer revenues, while societal cost is defined as the cost to consumers minus producer surplus:

$$CTC_c = R_{EOM,c} + R_{CM,c}, \quad SC_c = CTC_c - PS_c \quad \forall c \in C \quad (4.8)$$

Chapter 5

Results and discussion

As explained in Section 4.3, this thesis evaluates the resulting capacity prices and investment mixes across sixteen scenarios. Particular attention is given to case 1 (the current design) in Section 5.1, case 0 (single-year contracts for all technologies) in Section 5.2, and case 15 (15-year contracts for all technologies) in Section 5.3, as well as to the intermediate compromise cases. Subsequently, Section 5.4 analyzes the effects of the investment outcomes in these cases on total electricity market costs for consumers and producer surplus, while Section 5.5 examines the impact of the risk aversion parameters on the results. Finally, Section 5.6 discusses the main findings.

To introduce the results of the different cases, Figure 5.1 provides an overview of the resulting capacity prices and investment mixes. A clear decrease in the capacity price can be observed from case 0 to case 1. In this transition, modern CCGT capacity ("Gas" in the figures) and lithium-ion BESS capacity ("BESS" in the figures) move from one-year contracts to 15-year contracts. This eradicates their exposure to future capacity price uncertainty, as from case 1 onward they are only exposed to uncertainty in energy-only market revenues. Beyond case 1, the decrease in capacity price becomes less pronounced, as zinc production demand response capacity ("Zinc" in the figures) gradually gains access to longer-term contracts. As a result, its risk premium decreases from case to case, allowing it to bid more competitively. A final important observation is that zinc demand response investment reaches its lowest level in case 1. In this case, zinc faces the largest relative competitive disadvantage, as it remains exposed to full future capacity price uncertainty through one-year contracts, while gas-fired power plants and BESS benefit from 15-year contracts.

5.1 Current contract duration setup

Figure 5.2 provides an overview of the auction results for the approximation of the current Belgian setup, referred to as case 1. The auction clears at a capacity price of €46 014/MW_d (derated MW). Given that clearing prices in Belgian capacity market auctions for delivery periods between 2025 and 2027 ranged from €14 013/MW_d to €69 900/MW_d [13, 12], this represents a plausible estimate.

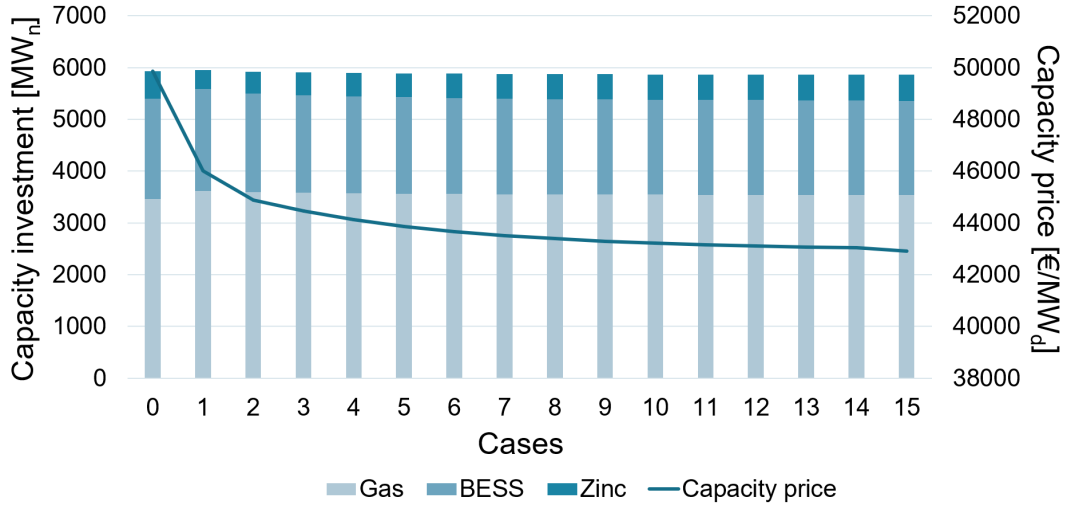


FIGURE 5.1: Installed capacity and capacity price by case.

Modern CCGT capacity dominates the newly built capacity mix, accounting for 75% of the derated capacity. Battery energy storage systems account for a derated share of 17%. It is important to note that BESS technologies have a relatively low derating factor of 37%. Despite nearly 2 GW_n of installed lithium-ion BESS investment, their contribution to the derated capacity mix hence remains limited. Zinc production demand response accounts for the smallest share of derated capacity investment at 8%. This is mainly driven by its relatively high investment cost, and to a lesser extent by the additional risk premium associated with future capacity price uncertainty.

The stacked bar chart illustrates the composition of the bid prices. The total cost per derated MW is calculated as the annualized investment cost, plus the risk premium on EOM and CM profits ($\gamma \cdot CVaR$), minus the expected EOM profits corrected through the EOM profit adjustment term scaled by the invested capacity ($CPC_p \cdot x_p$). Due to this profit correction term, the required capacity price is equal across all three technologies, as discussed further in relation to Figure 5.3. BESS experiences substantially higher EOM profits per derated MW compared to zinc DR due to its low derating factor, as it has almost three times more nominal installed capacity per derated MW than zinc DR. Despite not being exposed to capacity price uncertainty, gas-fired power plants exhibit the largest risk premium. This is because their EOM profits are highly sensitive to variations in the economic dispatch scenarios (gas price, carbon price, renewable generation capacity, and electricity demand). Fluctuations in EOM profits are substantially larger than those associated with future capacity prices and therefore contribute more strongly to the total risk premium. For gas-fired capacity, the range between the highest and lowest EOM profit scenario amounts to €330 175/MW_n, whereas the corresponding range

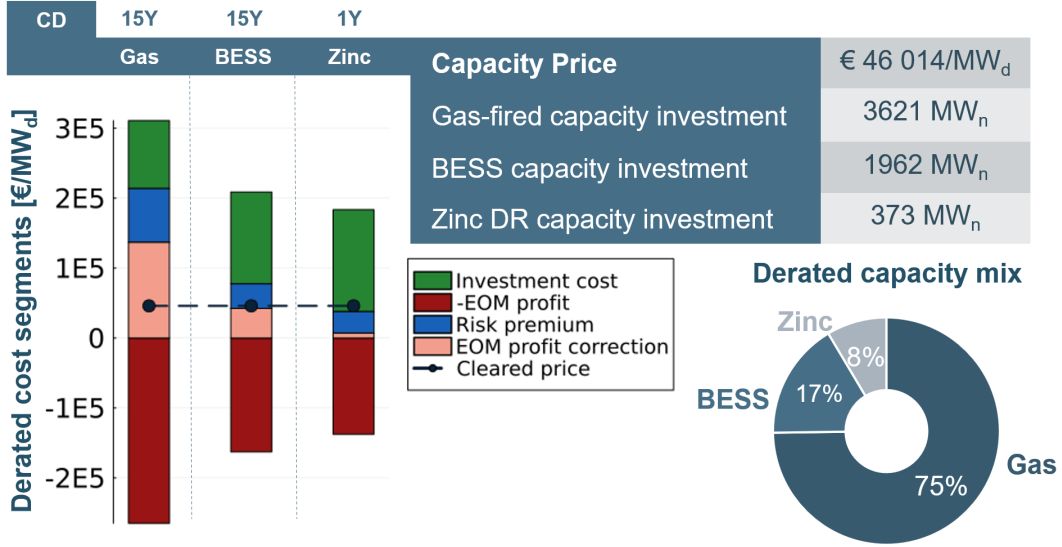


FIGURE 5.2: Stacked bar chart of cost segments defining the capacity bid by technology (left), capacity price and total investment (top right), and share of derated capacity investment by technology (bottom right) for case 1.

in future capacity price revenues is only €82 825/MW_n ($2 \cdot F_{gas} \cdot \lambda$). The effect of including or excluding capacity price uncertainty for gas-fired capacity and BESS is further discussed in Section 5.2 and Section 5.3, respectively.

Figure 5.3 shows the aggregate supply curve of the capacity market auction in case 1. This aggregate supply curve is constructed by horizontally summing the individual supply curves of all participating technologies. Existing installed capacity is modeled as perfectly inelastic supply, as these units are assumed not to require additional capacity revenues to remain operational. In contrast, the supply curves of the three new investment technologies are upward sloping. This upward slope is caused by the EOM profit correction term ($CPC_p \cdot x_p$): as more capacity of a given technology is invested, competition within that technology increases, reducing its expected EOM profits per MW and therefore increasing the required capacity price. The supply curve of gas-fired capacity starts at a strongly negative bid price. This indicates that, without accounting for the reduction in EOM profits due to additional investments, expected EOM profits are significantly higher than the combined annualized investment cost and risk premium. However, as more gas-fired capacity is installed, the $CPC \cdot x_{gas}$ correction increasingly reduces expected EOM profits, causing the required bid price to rise. BESS capacity only enters the capacity mix once the capacity price exceeds €3 588/MW_d. Zinc demand response enters the market only when the procured capacity volume approaches the capacity target, reflecting its comparatively higher initial bid price.

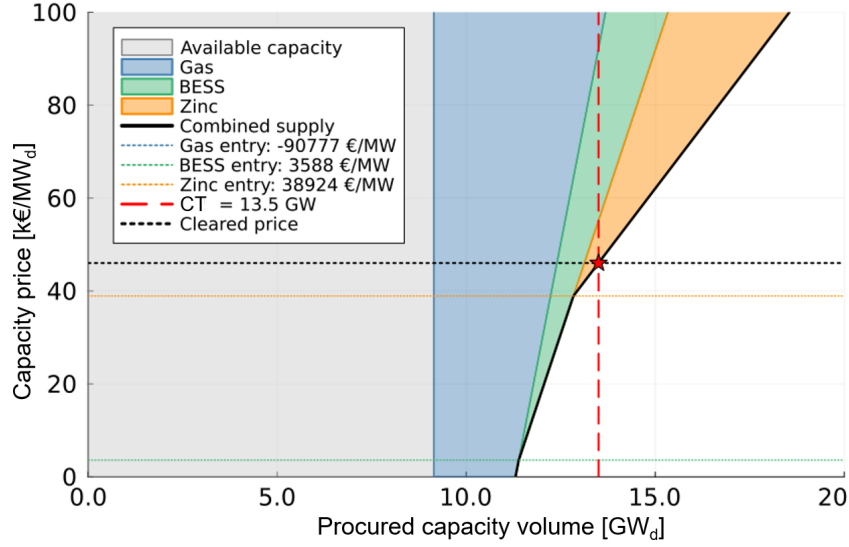


FIGURE 5.3: Aggregate capacity market supply curve constructed from the cumulative bid price-volume slopes of the participating technologies.

The slopes of the technology supply curves are determined by both the EOM profit correction factor and the derating factor, resulting in a slope equal to CPC/F_p^2 . This leads to a slope of $\text{€}42.0/\text{MW}_d^2$ for gas-fired capacity, $\text{€}19.0/\text{MW}_d^2$ for zinc demand response, and $\text{€}58.4/\text{MW}_d^2$ for BESS. The particularly steep slope of BESS is mainly driven by its low derating factor. The relatively low slope of zinc demand response makes its market share highly sensitive to changes in market conditions, as small variations in the procured capacity volume can either quickly move zinc DR out of the market or significantly increase its investment level. In contrast, the steep slope of BESS results in more stable capacity investment levels. The initial bid entries of the three technologies are affected by their respective risk premiums. The effect of these risk premiums on the supply curves is discussed further in Section 5.2.

Figure 5.4 shows the average electricity price for each quarter hour of a day in the reference year 2033 for the central economic dispatch scenario, after the capacity investments from case 1 become operational. The resulting residual demand and price profiles are within an expected range. It should be noted that the net discharge of the storage technologies, including zinc demand response in the economic dispatch model, appears relatively small. This is because charging and discharging patterns shift between different time steps from day to day, leading to a limited average net output over the full year.

5.2. Case without long-term contracts

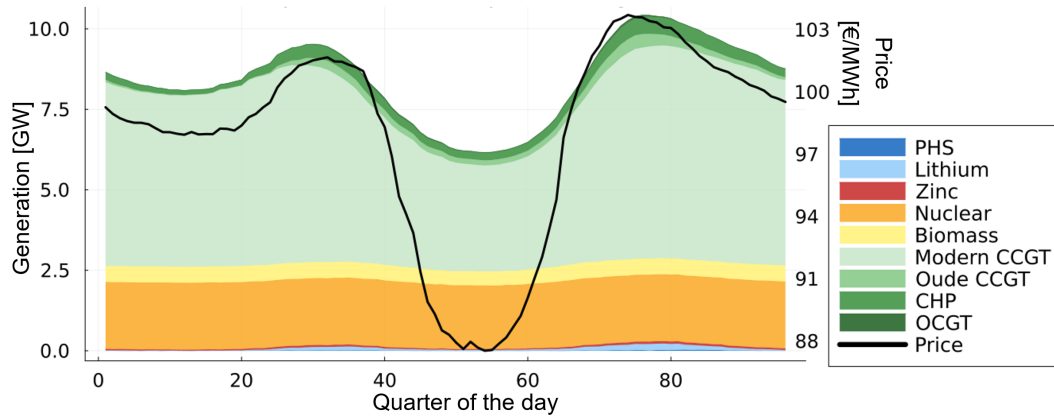


FIGURE 5.4: Average daily dispatch and price profile with generation represented cumulatively.

5.2 Case without long-term contracts

This section describes case 0, the hypothetical setup in which an equal playing field is created by removing long-term contracts entirely. As a result, all agents are exposed to both EOM and CM revenue uncertainty. The resulting auction outcomes are shown in Figure 5.5.

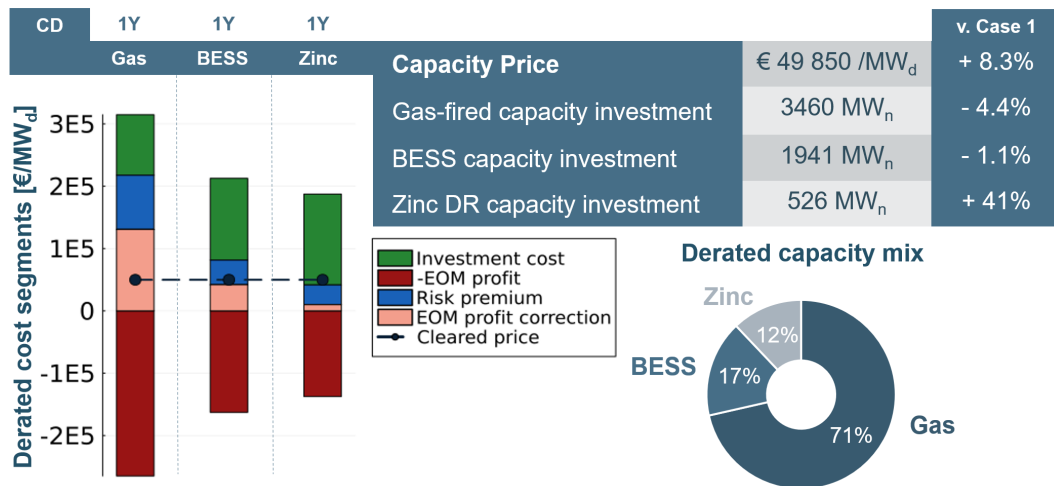


FIGURE 5.5: Stacked bar chart of cost segments defining the capacity bid by technology (left), capacity price and total investment (top right), and share of derated capacity investment by technology (bottom right) for case 0.

Due to the additional risk premium, the initial capacity bids of all technologies increase, resulting in an 8.3% increase in the cleared capacity price. This upward shift in the bid entries is illustrated in Figure 5.7. As expected, removing the risk protection provided by 15-year contracts for gas-fired capacity and BESS negatively affects their share in the capacity investment mix compared to zinc demand response. The increase in the risk premium, i.e. the additional revenue required to compensate for risk exposure, that is added to the initial capacity bids is positively related to $\lambda \cdot F_p$.¹ Since the derating factor of gas-fired capacity is significantly higher at 90% compared to 37% for BESS, the absolute increase in risk premium is larger for gas-fired capacity, as shown in Table 5.1. This explains the relatively larger reduction in gas-fired capacity investment. In contrast, zinc DR shows a 41% increase in capacity investment despite the more moderate increase in the capacity price. This is explained by the relatively low slope of CPC_{Zinc}/F_{Zinc}^2 , making zinc DR the most price-sensitive technology in the model.

TABLE 5.1: Risk premium comparison across cases 1, 0 and 15 for each capacity technology, and the change relative to the current design (case 1).

Risk Premium	Case 1	Case 0	Change	Case 15	Change
Gas-fired	77 001	86 923	+12.8%	77 001	=
BESS	35 147	39 441	+12.2%	35 147	=
Zinc DR	30 747	31 680	+3.0%	25 239	-17.9%

The table presents the risk premiums of the three capacity technologies across the three cases, together with the changes in cases 0 and 15 relative to case 1. Gas-fired capacity and BESS both experience a similar relative increase in risk premium, as CM revenue uncertainty is added to their risk calculations. Zinc demand response also sees a small increase in risk premium due to the higher cleared capacity price in case 0. Since CM revenue uncertainty scales with the capacity price, this leads to a higher risk premium. Before accounting for derating factors (i.e. when only considering the change in CVaR), the increase in the risk premium is smaller for gas-fired capacity than for BESS. This is because gas-fired technologies already experience relatively high volatility in EOM profits, making the additional effect of CM uncertainty less significant. However, once derating factors are taken into account, gas-fired capacity experiences the largest increase in effective risk premium. This is mainly driven by the very low derating factor of BESS.

5.3 Case with equal long-term contracts

This section describes case 15, the hypothetical setup in which an equal playing field is created by allowing zinc DR to participate in the same long-term contracts as gas-fired and BESS capacity. As a result, no technology is exposed to CM revenue uncertainty. The resulting auction outcomes are shown in Figure 5.6.

¹CVaR is calculated based on combined earnings per scenario: $EM_{ne,s} + F_{ne} \cdot \lambda \cdot \mu_{sc}$.

5.3. Case with equal long-term contracts

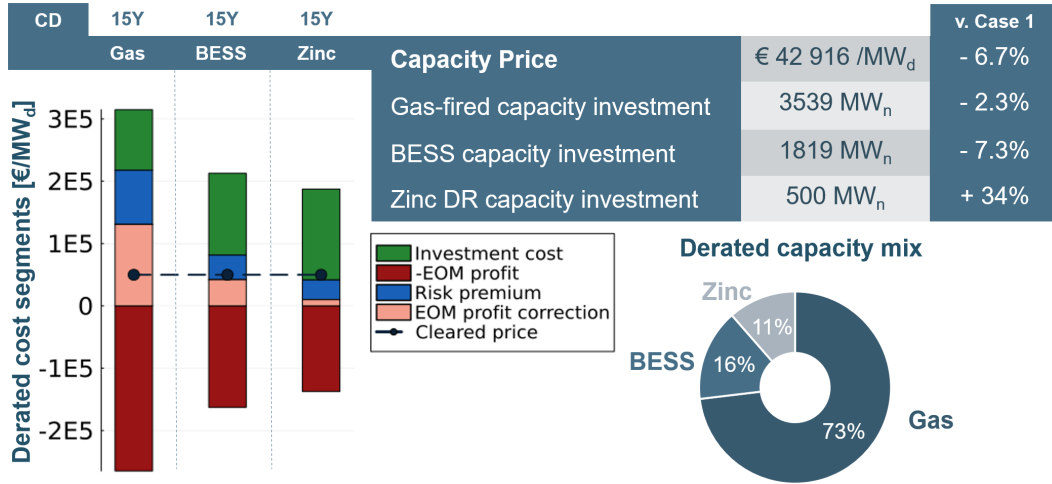


FIGURE 5.6: Stacked bar chart of cost segments defining the capacity bid by technology (left), capacity price and total investment (top right), and share of derated capacity investment by technology (bottom right) for case 15.

Due to the exclusion of capacity price uncertainty from the risk premium for zinc DR, it is able to bid more competitively, leading to a 6.7% decrease in the cleared capacity price. Once again, removing the relative risk disadvantage created by excluding zinc DR from 15-year contracts negatively affects investment in gas-fired and BESS capacity. As mentioned before, the relatively small reduction in BESS investment compared to gas-fired capacity is expected due to the steepness of its supply curve. However, the larger relative decrease in total installed BESS capacity shown in Figure 5.6 is partly explained by the fact that these values represent nominal installed capacity rather than derated capacity. Combined with the initially smaller BESS investment volume in case 1, this causes the relative percentage change to appear larger. Zinc DR benefits from the more equal allocation of risk, resulting in a 34% increase in capacity investment.

As shown previously in Table 5.1, CM revenue uncertainty is absent in this case while EOM profit uncertainty remains unchanged. As a result, the risk premiums of gas-fired and BESS capacity remain constant. In contrast, zinc demand response capacity shows a significant reduction in risk costs of nearly 18%. This reduction quantifies the effect of the additional CM revenue uncertainty present in case 1.

Figure 5.7 visualizes the cumulative supply curves for each case, together with the bid price entry points of each technology, represented by the horizontal lines. The cleared capacity price in each case is determined by the intersection of the capacity target threshold with the corresponding cumulative supply curve. The supply curves of gas-fired and BESS capacity are identical in cases 1 and 15, as these technologies remain eligible for 15-year contracts in both cases and therefore experience no change

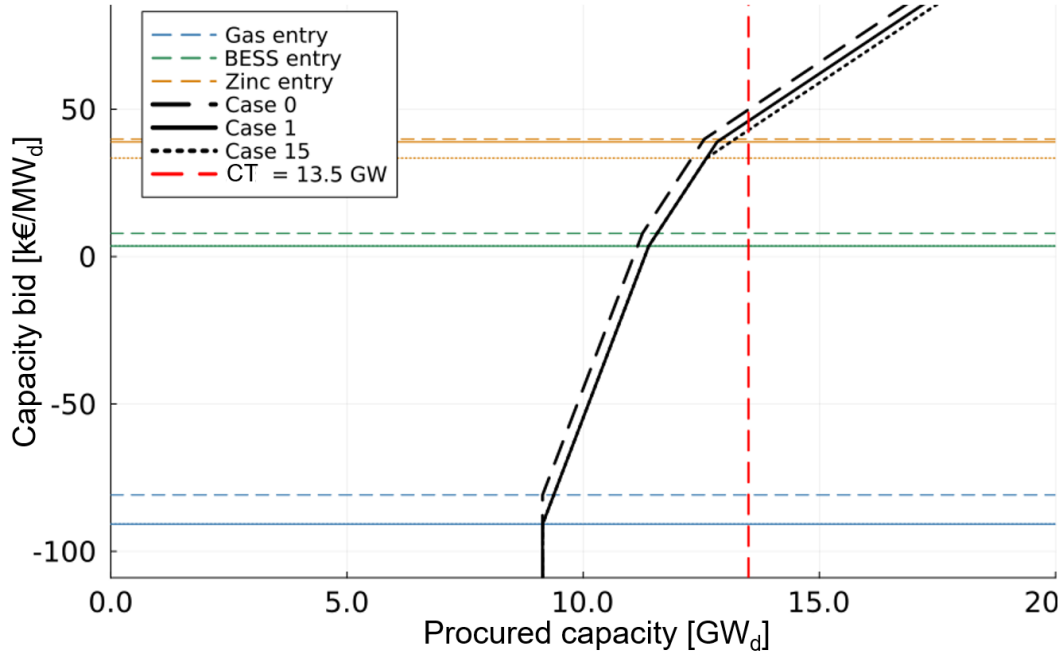


FIGURE 5.7: Cumulative supply curve and technology specific entry bid price for case 1, case 0 and case 15.

in CM revenue uncertainty. In case 0, however, both supply curves shift upward due to the additional CM risk premium that is added to their bid prices. As discussed previously and shown in Table 5.1, this upward shift is larger for gas-fired capacity than for BESS. Zinc DR exhibits a different behavior. Moving from case 1 to case 15 shifts the zinc DR supply curve downward due to the removal of CM revenue uncertainty. In contrast, the zinc DR bid entry point shifts slightly upward in case 0 relative to case 1. Although zinc DR already faced CM uncertainty in case 1, the increase in the cleared capacity price in case 0 raises expected CM revenues and therefore the uncertainty associated with these revenues, slightly increasing its risk premium. Additionally, because gas-fired capacity and BESS become less competitive in case 0 due to their increased risk premiums, zinc DR enters the cumulative supply curve at a lower cleared capacity price and therefore captures a larger market share, as it has the least steep supply curve slope. This explains why the increase in zinc DR investment from case 1 to case 0 is larger than the increase observed from case 1 to case 15.

Intermediate contract durations for demand response

Referring back to Figure 5.1, presented at the beginning of this chapter, it is valuable to also analyze the intermediate cases in which a compromise contract duration is offered to demand response, rather than only comparing the extreme cases of case

1 and case 15. In these intermediate cases, only the contract duration assigned to zinc demand response changes, while the contract duration for gas-fired capacity and BESS remains fixed at 15 years.

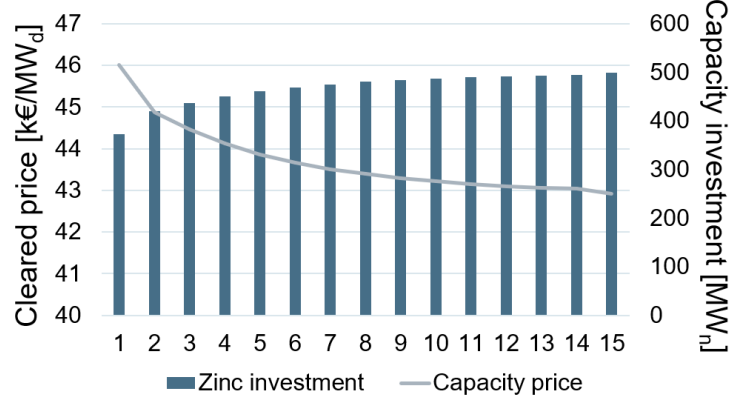


FIGURE 5.8: Capacity price and demand response capacity investment as a function of its contract duration.

Figure 5.8 specifically highlights zinc DR investment and the resulting capacity price as a function of the contract duration awarded to zinc demand response. Both curves show strong gains for relatively small increases in contract duration. Awarding contracts of 2, 3, or 5 years already increases zinc DR investment by 13%, 17%, and 24%, respectively, compared to the 34% increase achieved under a complete equalization of contract durations in case 15. A similar trend is visible for the capacity price. Awarding a 5-year contract already decreases the capacity price by 4.7%, compared to the total decrease of 6.7% obtained under 15-year contracts.

The diminishing returns associated with longer contract durations can be explained by two effects. First, due to discounting and risk aversion, capacity revenues in the first years of the contract are valued more strongly than revenues further in the future. Second, as the capacity price decreases, both the expected capacity revenues and the associated risk premium decrease as well. As a result, each additional year of capacity price certainty provides a smaller relative competitive advantage, leading to progressively smaller increases in capacity investment.

5.4 Economic evaluation of the cases

This section compares the economic costs and producer surpluses associated with the different cases. Figures 5.9, 5.10, and 5.11 show the average expected yearly producer revenues and costs for the different cases, calculated according to the metrics formulated in Section 4.4. Producer surplus is analyzed because it reflects the economic incentives for investment in new generation and capacity.

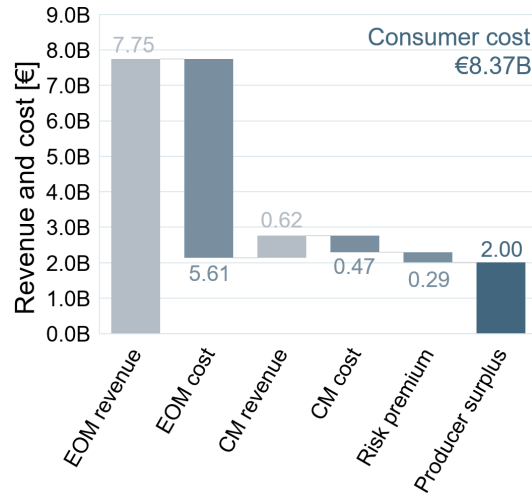


FIGURE 5.9: Waterfall plot of the producer surplus in case 1 taking into account the average economic dispatch scenario.

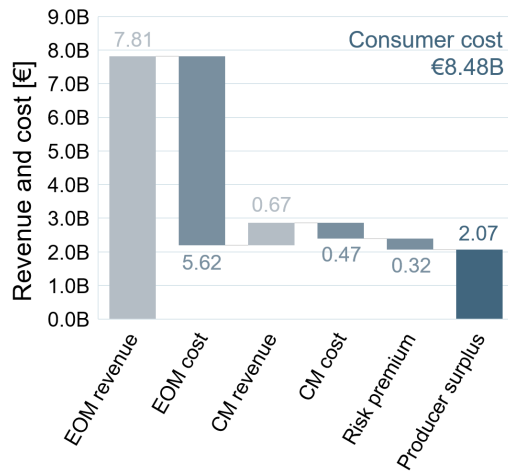


FIGURE 5.10: Waterfall plot of the producer surplus in case 0.

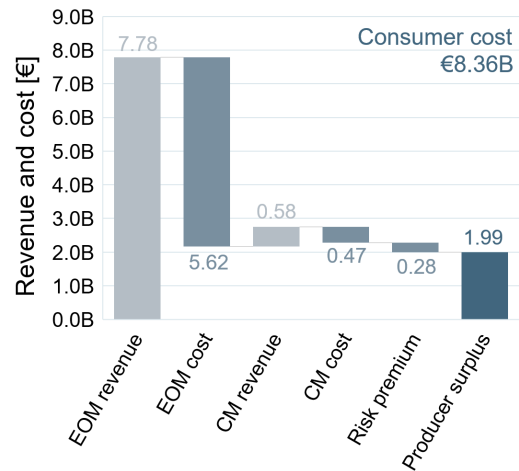


FIGURE 5.11: Waterfall plot of the producer surplus in case 15.

The energy-only market revenues and costs represent both installed generation capacity and newly built capacity investments. As a result, differences in EOM revenues between the cases remain relatively limited. Compared to case 1, total EOM revenues are 0.77% higher in case 0 and 0.41% higher in case 15. This indicates that the largest effect on electricity prices is caused by the share of modern CCGT capacity, as gas-fired power plants more frequently set the market price compared to BESS and zinc DR technologies. Since case 1 contains the largest share of modern CCGT capacity relative to combined BESS and zinc DR investment, it results in

the lowest average electricity prices.

Capacity market revenue shows the largest difference between the cases. The 16.2% higher capacity price in case 0 compared to case 15 leads to an increase of approximately €94M in yearly CM revenues. After subtracting the annualized investment costs and risk premiums of all installed capacity, the resulting yearly producer surplus amounts to €2.00B for case 1, €2.07B for case 0 (+3.47%), and €1.99B for case 15 (-0.57%).

A large share of these differences is explained by payments to existing installed capacity. Higher capacity prices increase CM revenues not only for newly built investments, but also for installed capacity that does not require additional investment support. Of the €94M increase in CM revenues between case 0 and case 15, the majority flows to installed capacity, as it accounts for 69.7% of the procured CT volume. These payments mainly create infra-marginal rents rather than additional investment incentives. In the Belgian capacity market design, this effect is constrained through the use of an intermediate price cap on existing capacity, limiting the CM revenues these units can receive.

These results support the common regulatory argument in favor of long-term contracts for new capacity investments, as lower required clearing prices reduce the consumer cost of the capacity market by constraining total CM expenditures. The total cost to consumers differs by approximately €121M between case 0 and case 15.

Comparing the most policy-relevant cases, namely case 1 representing the current Belgian setup and case 15 representing a setup in which zinc DR gains access to the same long-term contracts as generation and storage technologies, the results indicate a modest but clear economical benefit from extending long-term contracts to industrial demand response. The lower capacity price in case 15 reduces CM payments while simultaneously improving the competitiveness and investment share of zinc DR.

From a consumer expenditure perspective, case 15 reduces total consumer payments by approximately €9.9M compared to case 1. Although the lower capacity clearing price reduces CM payments by around €42M (a 6.7% reduction), part of this effect is offset by approximately €32M higher EOM expenditures caused by lower gas-fired capacity investment and consequently somewhat higher wholesale electricity prices. This highlights the interaction between the CM and EOM: lower capacity prices can reduce investment incentives and thereby increase electricity prices, while higher capacity prices may stimulate additional capacity investment and reduce EOM prices, as more capacity competes to meet electricity demand.

This effect, where reductions in capacity market costs are largely offset by increases in EOM costs, is also reflected in the societal cost (SC), which is calculated by subtracting producer surplus from total consumer expenditures. This results in an SC

of €6.367B for case 1, €6.409B for case 0, and €6.369B for case 15, corresponding to increases of 0.66% and 0.03%, respectively. Case 1 results in the lowest total societal cost, mainly due to lower EOM expenditures for consumers.

5.5 Sensitivity analysis of the degree of risk aversion

This section provides a sensitivity analysis of the two parameters influencing the risk premium and resulting capacity price. Figure 5.12 first shows the capacity price as a function of the CVaR weighting parameter γ . The effect of increasing γ is largest in case 0, followed by case 1, and smallest in case 15. This follows from the fact that the CVaR is highest in case 0 and lowest in case 15, reflecting the different levels of exposure to revenue uncertainty across the cases.

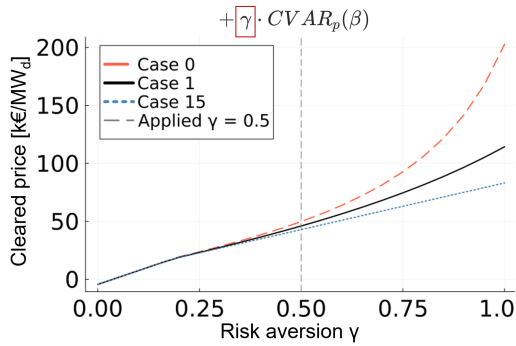


FIGURE 5.12: Capacity price as a function of the CVaR weighting parameter for the three cases.

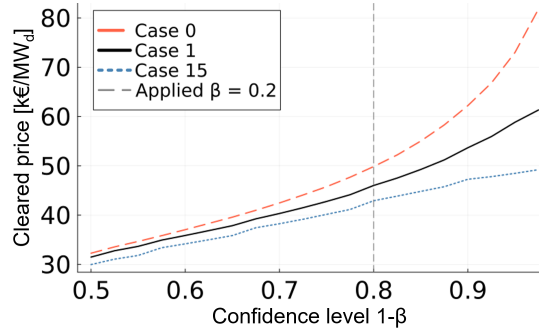


FIGURE 5.13: Capacity price as a function of the confidence level for the three cases.

A key result is the fact that the capacity price in case 0, and to a lesser extent in case 1, increases nonlinearly as a function of γ . This effect arises because, when CM revenue uncertainty is included in the CVaR calculation, the risk premium becomes partly dependent on the cleared capacity price itself. Since the cleared capacity price is simultaneously determined by the value of $\gamma \cdot CVaR$, a reinforcing feedback effect emerges between the risk premium and the auction clearing price. The relatively strong sensitivity of the capacity price to γ in the current setup represented by case 1 indicates the high economic value that capacity providers attach to reducing revenue uncertainty for their investment.

Similar trends can be observed in Figure 5.13, where the capacity price is plotted as a function of the confidence level. The confidence level determines which percentage of scenarios is considered non-critical in the CVaR calculation. Due to the circular dependence introduced by CM revenue uncertainty, the same nonlinear trend for case 1 and case 0 is visible here.

5.6 Discussion

Asymmetric contract durations distort long-term investment incentives and thereby influence the resulting capacity mix. This final section summarizes the work conducted in this thesis and discusses the main findings. It subsequently outlines the simplifications and limitations of the adopted modeling approach. Finally, several directions for future research are highlighted that may contribute to a more complete assessment of the issue and support potential policy implementation.

This thesis set out to answer the research question: *“What is the effect of unequal capacity market contract durations on the long-term capacity mix?”* To address this question, a framework was developed to assess the effect of contract duration on capacity market auctions and the resulting investment decisions. Applying this framework to a simplified representation of the Belgian electricity and capacity market proved particularly relevant, as recent policy discussions have questioned whether demand response investments are disadvantaged by their inability to qualify for long-term contracts. The results show that asymmetry in contract durations can significantly shape the resulting capacity mix. More specifically, for the implemented Belgian case study, the findings indicate that demand response integration in the electricity market, and its contribution to achieving adequate capacity levels, can be significantly supported by offering equal access to long-term contracts for new investments.

The analysis showed a significant impact of contract duration design on capacity market outcomes. Both cases with equal contract durations resulted in a strong relative increase in demand response capacity investment. This was observed both in the case where long-term contracts were completely removed for all technologies and in the case where all technologies received 15-year contracts. However, the case without long-term contracts introduced additional CM revenue uncertainty for all technologies, leading to significantly higher risk premiums and consequently higher capacity prices. Although the resulting savings in capacity market expenditures were offset by higher energy-only market costs in our analysis, the findings nevertheless reiterate the classical regulatory argument in favor of long-term contracts, as policymakers tend to prioritize keeping capacity market expenditures low.

For this reason, the thesis also analyzed a compromise between the two most policy-relevant cases: the current setup, in which demand response is excluded from 15-year contracts, and a fully equalized setup where all technologies receive the same long-term contracts. The compromise consists of awarding demand response contracts longer than one year, but shorter than the full 15-year duration. These intermediate contract durations already showed significant effects. Awarding 5-year contracts, only one third of the full 15-year duration, already realized almost 70% of the additional demand response investment and capacity price reduction achieved under full contract equalization. These results demonstrate the value that even partial capacity payment certainty can provide, both to the investor and regulator, as it

aims to keep capacity prices low.

The modeling approach used in this thesis contains several simplifications. Five important limitations are listed below:

- Each technology is represented by a single overnight investment cost rather than a range of heterogeneous investors with different investment costs. In particular, the investment cost for demand response was intentionally set relatively high, as it is difficult to determine what share of industrial investments should be attributed to additional capacity provision rather than operational optimization, while the objective was to model the behavior of an emerging and relatively expensive technology.
- The model determines total investment based on one representative future year of EOM profits, rather than modeling a gradual evolution of investments over time. In reality, investment would likely occur incrementally, potentially causing stronger year-to-year fluctuations in auction competition and cleared prices, as the introduction of a single large-scale investment, such as a major battery park or gas-fired power plant, could significantly affect market outcomes in a given period.
- Demand response is modeled in the economic dispatch framework as a virtual battery with perfect efficiency. In practice, industrial demand response is constrained by economic, operational, and technical considerations that differ across industrial processes. A more detailed implementation of these constraints could reduce the profitability of demand response.
- The model assumes that investment lifetime coincides with the 15-year capacity market horizon. In reality, technologies such as gas-fired power plants may continue operating beyond this period, albeit with additional maintenance costs, while some demand response investments may have shorter effective lifetimes.
- EOM and CM uncertainty scenarios are treated as independent. In practice, correlations between both markets may exist. For example, higher renewable penetration could simultaneously reduce EOM profits for gas-fired power plants while increasing the profitability and competitiveness of battery storage in the capacity market, thereby linking low-profit scenarios for gas-fired power plants across both markets.

Future research could further refine this framework for a specific demand response investment case by incorporating more realistic assumptions regarding expected revenues, costs, and investment lifetimes. This would allow for a more accurate assessment of realistic bid prices and the reduction in risk costs that longer-term contracts may provide for a specific investment.

From a policy perspective, further research could also evaluate the additional regulatory verification and monitoring costs associated with granting long-term contracts to demand response providers. As noted in the literature review, important challenges remain regarding the verification and monitoring of industrial demand response facilities [9]. Quantifying these implementation costs would allow policymakers to compare them against the societal benefits of multi-year contracts for demand response identified in this thesis. Finally, this thesis focused on the risk costs experienced by capacity providers when they are excluded from long-term contracts. However, as discussed in the literature, long-term contracts effectively shift part of this risk from investors to the regulator or consumer. Further research could therefore assess the economic value and societal cost of this risk transfer itself.

Chapter 6

Conclusion

This thesis has examined the effect of unequal capacity market contract durations on the long-term capacity mix. As discussed in Chapter 2, European policymakers and regulators have increasingly supported the implementation of CRMs to safeguard long-term generation adequacy. This has led to a growing number of capacity markets across Europe, each characterized by different design choices regarding contract durations and eligibility criteria. Many capacity markets combine annual contracts with longer-term contracts for new investments. However, demand response technologies are often not granted the same long-term contract durations as generation and storage technologies.

Chapters 3 and 4 introduced an equilibrium-based capacity market model, with energy-only profit estimates provided by a separate economic dispatch model, together with a Belgian case study comparing three contract duration frameworks: a uniform one-year contract structure (case 0), the current partially differentiated structure with fifteen-year contracts for gas-fired capacity and BESS but one-year contracts for demand response (case 1), and a uniform fifteen-year contract structure (case 15). Demand response was represented through a zinc electrolysis-based demand response resource modeled as a virtual battery.

The analysis presented in Chapter 5 provides several important insights into the role of contract duration design within capacity markets. First, the results demonstrate that contract duration significantly influences the auction clearing price and the resulting capacity investment mix.

Second, the results show that equal contract durations substantially increase the competitiveness and participation of demand response within the capacity portfolio. When demand response receives the same long-term contracts as gas-fired capacity and BESS, its market share increases considerably because the improved revenue certainty lowers its effective risk premium. This finding highlights that differentiated contract durations can unintentionally favor certain technologies over others.

Third, this thesis demonstrates that long-term contracts provide substantial economic value by reducing capacity market clearing prices. By lowering investment revenue risk, longer contracts reduce bid prices. Although the model suggests that reductions in CM expenditures may be partially offset by higher EOM expenditures, the results nevertheless confirm the effectiveness of long-term contracts in reducing required capacity market costs.

Finally, the results indicate that even partially extending contract durations for industrial demand response already leads to substantial increases in demand response participation within the capacity mix and reductions in capacity prices. This suggests that policymakers may capture a large share of the benefits associated with long-term contracts without requiring demand response technologies to receive contract durations as long as those granted to gas-fired capacity and BESS.

Several directions for future research remain. First, the model could be applied more precisely to a specific instance of demand response investment to analyze the effect contract duration has on its economic viability. Second, the risk cost of granting long-term contracts should be analyzed from the perspective of the regulator, as this effectively represents a transfer of risk exposure from the producer to the regulator and, indirectly, to consumers. Finally, the cost of monitoring and verifying compliance of demand response facilities should be assessed in order to compare these costs with the benefits that long-term contracts for demand response can provide, as demonstrated in this thesis. Overall, this thesis shows that contract duration design constitutes an important component of capacity market design, with a significant influence on investment outcomes and the resulting capacity mix. The results suggest that policymakers may benefit from further evaluating broader access to long-term contracts for demand response technologies.

Appendices

Appendix A

Variable cost of gas-fired power plants

Table A.1 presents the main parameters of the gas-fired power plant fleet modeled in the economic dispatch model. The carbon intensity parameter is calculated by dividing the carbon intensity of natural gas, assumed to be 0.202 tonCO₂eq/MWh_{th}, by the plant efficiency. An exception is made for CHP units, for which a carbon intensity of 0.3 tonCO₂eq/MWh_e is adopted based on [33].

TABLE A.1: Gas-fired power plant characteristics in the economic dispatch model.

Plant (type)	Capacity (MW)	Carbon intensity (tonCO ₂ eq/MWh _e)	η_i [%]
Modern CCGT (Gas)	4000	0.326	62
Old CCGT (Gas)	2500	0.388	52
OCGT (Gas)	2000	0.505	40
CHP (Gas)	1500	0.3	44

The fuel cost of each gas-fired power plant is calculated by dividing the gas price (p_{gas}) by the corresponding plant efficiency (η_i). The resulting fuel costs are reported in Table A.2.

TABLE A.2: Fuel costs of gas-fired power plants in the economic dispatch model.

Fuel cost (€/MW _e)	$p_{gas} =$ €22.5/MW _{th}	$p_{gas} =$ €30/MW _{th}	$p_{gas} =$ €37.5/MW _{th}
Modern CCGT	36.29	48.38	60.48
Old CCGT	43.27	57.69	72.12
OCGT	56.25	75.00	93.75
CHP	51.14	68.18	85.23

A. VARIABLE COST OF GAS-FIRED POWER PLANTS

The carbon cost of each gas-fired power plant is calculated by multiplying the EU ETS price (α) by the corresponding plant carbon intensity. The resulting carbon costs are reported in Table A.3.

TABLE A.3: Carbon costs of gas-fired power plants in the economic dispatch model.

Carbon cost (€/MW_e)	$\alpha =$ €80/tonCO₂eq	$\alpha =$ €140/tonCO₂eq
Modern CCGT	26.08	45.64
Old CCGT	31.04	54.32
OCGT	40.04	70.70
CHP	24.00	42.00

The total variable cost of a gas-fired power plant is calculated as the sum of the fuel cost, carbon cost, and a variable operating and maintenance cost ($O\&M$) of €10/MWh_e.

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Code of conduct and transparency statement on the use of GenAI for KU Leuven-students (academic year 2025–2026)

Generative AI (GenAI) assistance tools can be used to generate various types of content, including text, images, code, video, music, or combinations thereof. Common examples of such tools include ChatGPT, Google Gemini, Microsoft Copilot, Midjourney, Claude.ai, Perplexity.ai, and DALL·E, among others.

This code of conduct is a tool that helps students to be transparent about the use of GenAI and fits within the university's principles on academic integrity.

Important guidelines and remarks

- **Sensitive or personal data:** Some GenAI tools protect your input and sensitive or personal data better than others. There is often no transparency on what the owners of the AI applications do with the data entered. Therefore, **do not enter sensitive or personal data in free GenAI tools.** More info about what sensitive and personal data are, is described in the three confidentiality levels of the KU Leuven data classification model (non-confidential, confidential, strictly confidential). For confidential data you should preferably use **M365 Copilot Chat with your KU Leuven account.** If you use another GenAI tool, you must be **absolutely certain** it does **not store or reuse the data you enter.** **Try to avoid entering these data. Do so only if strictly necessary, and only to the extent required. For personal data, work with anonymous or pseudonymized data.** Additionally, in case of strictly confidential data this should first be discussed with the teaching staff of the course or your thesis supervisor.
- **Copyrighted materials:** For lawfully obtained copyrighted material you should preferably use **M365 Copilot Chat with your KU Leuven**

account. If you use another GenAI tool, you must be **absolutely certain** it does **not store or reuse the data you enter**.

- GenAI assistance may not be used for data or topics covered by a Non-Disclosure Agreement (NDA). Even in the absence of an NDA, certain information may still need to be treated as confidential—for example, due to regulatory requirements or the risk of significant harm to the university if disclosed. In case of doubt, check with your teaching staff or supervisor.
- If your master’s thesis is under embargo, you should first discuss with your supervisor whether the use of GenAI is permitted.
- Before using a GenAI tool, always consider whether its use is responsible, including from a sustainability perspective (e.g. when using GenAI as a search engine, language assistant, ...).
- **Take a scientific and critical attitude** when interacting with GenAI assistance and interpreting its output, that may not always be correct.
- As a student you are responsible for complying with Article 84 of the Regulations on Education and Examinations: your report or thesis should reflect your own knowledge, understanding and skills. Be aware that plagiarism rules also apply to (work that is the result of) the use of GenAI assistance tools.
Exam Regulations Article 84: *“Every conduct individual students display with which they (partially) inhibit or attempt to inhibit a correct judgement of their own knowledge, understanding and/or skills or those of other students, is considered an irregularity which may result in a suitable penalty. A special type of irregularity is plagiarism, i.e. copying the work (ideas, texts, structures, designs, images, plans, codes , ...) of others or prior personal work in an exact or slightly modified way without adequately acknowledging the sources. Every possession of prohibited resources during an examination (see article 65) is considered an irregularity.”*
- In order to maintain academic integrity and avoid plagiarism, **more information about being transparent on the use of GenAI assistance and about correctly citing and referencing GenAI** can be found on this website for students (Dutch/English).
- **Additional reading: KU Leuven guidelines on responsible use of Generative AI tools, and other information** (Dutch/English)

A few final words

If you are uncertain whether or not you should declare your use of GenAI tools, we suggest that you discuss this with your instructor or supervisor. It is always safer to declare GenAI use, even when it is not strictly required. However, declaring GenAI use does not entail that its use is

allowed; the right column in the table below provides more detailed instructions in this regard (code of conduct).

Moreover, advanced AI tools are evolving rapidly, and their capabilities have expanded significantly in a short period of time. As a result, we do not yet have all the answers about their responsible use. Finally, it is important to follow-up on the most recent evolutions in AI technologies, to have an open mind but also to be a bit cautious, to communicate with instructors, teaching assistants, supervisors and peers, to be as transparent as we can, and to learn together as we move along.

Student name: Arent De Wit

Student number: r0856595

Please indicate with "X" whether it relates to a course assignment or to the Bachelor's or Master's thesis:

☐ This form is related to a **course assignment**.

Course name: **Course number:**

This form is related to my ☐ **Bachelor's** or ☒ **Master's thesis**.

Title Bachelor's or Master's thesis: The impact of contract duration in capacity markets on the long-term capacity mix

Daily supervisor: dr. ir. J. Meus, ir. E. Chambard

Please indicate with "X":

☐ I **did not use** any GenAI assistance tool.

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GenAI assistance used as/for:	Name of the GenAI tool(s) used If helpful, also describe in which way you were using GenAI related to what is specified as code of conduct.	Code of conduct: For each of the categories below, always take into account the important guidelines and remarks mentioned above (e.g. copyrighted data, sensitive or personal data,...).
As a language assistant for reviewing or improving texts I wrote myself	<i>ChatGPT for rewriting and improving sentences, which I wrote myself first</i>	This use is similar to using spelling and grammar check tools. In general, you do not have to refer to such kind of GenAI use in the text. However, be careful: When using GenAI tools on texts you did not write yourself to improve the text, you have to refer to the original source or author, otherwise you are committing plagiarism and thus an irregularity.
As a paraphrasing tool	/	This use is allowed except when it is prohibited by the teacher or the program of study. You may paraphrase your own text or texts by an author other than yourself and take inspiration from what a GenAI tool or another tool suggests (unless it is not allowed). In general, you do not have to refer to such kind of GenAI use or other paraphrasing tools in the text. However, be careful: If it entails text by an author other than yourself, you are not allowed to include that paraphrased text without reference to the original source or author. Without such reference, you would be committing plagiarism and thus an irregularity.

For translation aid to improve texts I wrote myself or to better understand text from others	/	This use is allowed except when it is prohibited by the teacher or the program of study. It is similar to using translation tools (Google translate, DeepL, ...). In general, you do not have to refer to such kind of GenAI use in the text. However, be careful: • You are not allowed to include that translated text without reference to the original source or author. Without such reference, you would be committing plagiarism and thus an irregularity. • Always check the translated text for correctness and meaning.
As a search engine to get information on a topic or to search for existing research on the topic	/	This use is similar to e.g. a Google search or checking Wikipedia. If you write your own text based on this information, you do not have to refer to the use of GenAI in the text. You only have to refer to the existing research and references you have checked and used (without such references you would be committing plagiarism and thus committing an irregularity). However, be careful: • Be aware that the output of the GenAI tool cannot be guaranteed as a 100% reliable source of information. The output may not be entirely correct and/or be limited due to the databases it uses. Moreover, knowledge evolves and may change over time; therefore, the database of the GenAI tool may not be up to date. Therefore, verify the information and do not just copy-paste it as you should understand and critically process everything you are writing.

For literature search	<i>Elicit was used only to help assess the existence of relevant literature related to the research topic.</i>	This use is comparable to e.g. a Google Scholar search. You do not have to refer to such kind of GenAI use; you only have to refer to the literature references you have checked and used (without such references you would be committing plagiarism and thus committing an irregularity). However, be careful: • Be aware that the search output is restricted to the database the GenAI tool is built on. After this initial search, look for scientific sources and conduct your own analysis of the source documents. Interpret, analyse and process the information you obtained; verify it and do not just copy-paste it as you should understand and critically process everything you are writing. • Be aware that some GenAI tools may output no or wrong references. As a student you are responsible for further checking and verifying the absence or correctness of references; do not just copy-paste it.
For generating programming code	<i>Claude to help with the JuMP implementation and visualization of the model, ChatGPT for LaTeX in the construction of the thesis.</i>	Use of GenAI for coding is allowed except when it is prohibited by the teacher or the program of study. If used for coding, correctly mention the use of GenAI assistance in accordance with the instructions on the page on being transparent about the use of GenAI.

For new ideas	generating (research)	/	This use of GenAI is allowed except when it is prohibited by the teacher or the program of study. Correctly mention the use of GenAI assistance in accordance with the instructions on the page on being transparent about the use of GenAI. Be careful: • Further verify in this case whether the idea is novel or not. It is likely that it is related to existing work. If so, that existing work should be correctly referenced in the text (without such reference you would be committing plagiarism and thus committing an irregularity).
For synthetic data	generating	/	Use of GenAI for generating synthetic data is allowed, provided that it is methodologically and ethically justifiable, except when it is prohibited by the teacher or the program of study. Always correctly mention the use of GenAI assistance in accordance with the instructions on the page on being transparent about the use of GenAI. Be careful: • Always carefully evaluate the generated synthetic data for quality and possible bias since the output is highly dependent on the quality of the data on which the models are trained.

For generating blocks of text (other than the allowed use without referencing mentioned above)	/	According to Article 84 of the Regulations on Education and Examinations your text should allow to correctly and properly assess your own knowledge, understanding and skills. Therefore, inserting blocks of text without quotes and a reference to GenAI assistance in your work is not allowed. Be careful: • If it is really needed to insert a block of text from a GenAI tool, for instance because of the nature of your assignment, mention it as a citation by using quotes and correctly mention the use of GenAI assistance in accordance with the instructions page on being transparent about the use of GenAI. • However, in general, such GenAI use should be kept to an absolute minimum; you should always check the original sources.
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Other use (specify here; this may also include a combination of types of use mentioned above):	/	To make sure other use of GenAI is allowed within the course or thesis, and if so, the conditions that may apply, contact the teaching staff of the course or the supervisor of the thesis beforehand and explain the intended GenAI use. Also inform the programme director. Motivate how you would comply with Article 84 of the exam regulations. Explain the use and the added value of the AI tool you consider to use and how it is in accordance with the assignment or thesis and the KU Leuven guidelines on responsible use of Generative AI tools. Depending on the kind of GenAI use, it may be needed to properly reference it in the text, in accordance with the instructions page on being transparent about the use of GenAI.
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