

Louvain School of Management

Economic Evaluation of the Belgian Capacity Remuneration Mechanism

*A Simulation-Based Assessment of Reliability
Options under Different Scenarios for 2030*

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Abstract :

Over the past decade, Capacity Remuneration Mechanisms (CRMs) have been introduced in several countries, including Belgium, to ensure resource adequacy in electricity markets. However, the literature continues to debate the economic efficiency and calibration of CRMs, particularly regarding risks of over-procurement, coordination issues between national mechanisms and the influence of regulatory design choices on market outcomes. This thesis contributes to this discussion by evaluating one specific financial dimension of the Belgian CRM for the 2030 delivery horizon: the relationship between capacity remuneration and the repayment obligations associated with reliability options.

Future electricity price trajectories are simulated under alternative scenarios using a Monte Carlo framework to estimate expected reliability option repayments and evaluate the resulting payment gap across scenarios.

The results suggest that reliability option repayments remain below capacity remuneration in most scenarios and only exceed it under severe market stress conditions. These findings indicate that such repayments are strongly influenced by uncertainty in future electricity prices and appear more sensitive to persistent scarcity episodes than to ordinary market fluctuations. The alternative scenarios simulated within the scope of this study, do not suggest an under-remuneration through the CRM mechanism itself. The results do not allow to draw definitive conclusions concerning whether the Belgian CRM over-remunerates capacity providers overall, since broader economic outcomes also depend on investment incentives, technology-specific costs and additional revenue streams beyond the scope of this analysis.

At the same time, the results suggest that increasing renewable penetration may reinforce adequacy and flexibility challenges rather than reduce the relevance of capacity mechanisms. In this context, the key issue may become less whether CRMs are needed, than which types of flexible resources they incentivise or support.

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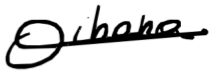
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1. Introduction

Maintaining security of electricity supply while preserving efficient market incentives has become a central challenge for European electricity markets. Although energy-only markets are designed to ensure generation adequacy through price signals, concerns have emerged regarding whether electricity market revenues alone provide sufficient incentives to maintain or develop reliable capacity (Newbery, 2020; Lindell, 2025). In response, several European countries introduced Capacity Remuneration Mechanisms (CRMs), designed to ensure resource adequacy by remunerating the availability of capacity alongside electricity market participation (European Commission, 2022).

Belgium implemented a Capacity Remuneration Mechanism based on reliability options (Elia, n.d.). Under this design, capacity providers receive a fixed capacity payment in exchange for committing available capacity but must reimburse part of their revenues whenever electricity prices exceed a predefined strike price. Consequently, the economic value effectively retained from capacity contracts depends not only on the remuneration received but also on the future repayment obligations generated by reliability options. Since the repayment obligations depend directly on future electricity prices, the share of capacity remuneration effectively retained by providers remains uncertain at the time capacity contracts are awarded

Although CRMs are introduced to improve security of supply, their economic efficiency, calibration and coordination across European electricity markets remain actively debated in the literature, particularly with regard to risks of over-procurement and distorted investment incentives (Lindell, 2025).

This thesis originated from the broader question of whether the remuneration received by capacity providers remains proportionate to the financial obligations associated with reliability options and whether the mechanism could potentially contribute to situations of over- or under-remuneration of participating capacity. Rather than providing a complete assessment of the overall profitability or efficiency of the Belgian CRM, this thesis evaluates one specific financial dimension of the mechanism for the 2030 delivery horizon. More specifically, the analysis estimates the expected payment gap, defined as the difference between the remuneration received through the Belgian CRM and the expected repayments associated with reliability options. To estimate this payment gap, future electricity price trajectories for 2030 are simulated using a Monte Carlo framework under four alternative scenarios for the Belgian electricity system. Simulated prices are translated into expected reliability option repayments and compared with the remuneration associated with Belgian capacity contracts.

This approach provides insights into how different market conditions might influence repayment obligations and contributes to the broader discussion regarding the role and remuneration of the Belgian CRM.

2. Theoretical, Institutional and Market Framework

2.1 Security of Supply and Adequacy

2.1.1 Defining security of supply and adequacy

Security of supply can be defined as the ability of the electricity system to provide the quantity of electricity required by consumers under all circumstances, particularly during peak demand periods. It therefore refers to an expected level of system performance established by public authorities and constitutes a major issue in highly electrified economies, where any interruption of supply may lead to significant economic losses and affect essential services (FEBEG, 2026; Kapeller et al., 2026).

In recent European literature, this issue is increasingly approached through the concept of resource adequacy, that is, the ability of the available resources within a given area to meet electricity demand. Adequacy is therefore not limited to generation capacities alone; it also encompasses storage resources, demand-side response, and available import possibilities that can be mobilised to maintain the balance between supply and demand (Kapeller et al., 2026).

However, security of supply does not correspond to absolute reliability. From an economic perspective, public authorities rather seek to determine a level of residual risk considered acceptable in relation to the cost of the additional capacities required to reduce it (Kapeller et al., 2026). The objective is therefore not to eliminate any possibility of shortage, but to achieve a socio-economically optimal level of reliability. This approach implies that adequacy cannot be reduced to a simple comparison between installed capacity and expected consumption. It depends on the actual availability of resources, their location, their flexibility, and their ability to respond to technical, weather-related, or network-related uncertainties (Astier & Ovaere, 2022). This distinction constitutes the starting point of this analysis: the issue is not merely to have megawatts available, but to have reliable resources available when the system needs them.

2.1.2 Why adequacy is becoming a major issue again in Europe

One of the major findings of recent studies is that capacity adequacy, which had long been relatively unproblematic in Western Europe, has once again become a central issue. Following liberalisation, Europe still benefited from comfortable reserve margins inherited from the period of national monopolies, but these margins have gradually eroded over the last two decades. This evolution results from a combination of factors: strong support for variable renewable energy sources, downward pressure on wholesale prices, the early retirement of coal and nuclear units, regulatory uncertainty, and reduced incentives to invest in new thermal capacities (Larsen & van Ackere, 2023).

The rapid development of variable renewable energy sources, supported through renewable support policies in Europe, has profoundly transformed the structure of the European electricity system. The production of these technologies depends on weather conditions, seasons, and the time of day; consequently, their contribution to adequacy cannot be assimilated to their nominal capacity (Larsen & van Ackere, 2023; Elia 2024). At the same time, several studies emphasise that they may weaken incentives to invest in conventional thermal power plants, even though such plants remain necessary when renewable generation is low. A risk of underinvestment in dispatchable capacities may therefore weaken the long-term reliability of the system (Liebensteiner & Wrienz, 2020; Beck-Bang et al., 2026).

The issue of adequacy is therefore re-emerging not because Europe is mechanically lacking installed megawatts, but because the transformation of the electricity mix is changing both the availability and the effective value of these capacities at critical moments. Recent analyses at the European level confirm this diagnosis. Under certain scenarios, several electricity systems could exceed their reliability standards, particularly in the medium term, reflecting potential tensions in the balance between supply and demand (ENTSO-E, 2024).

The concept of *dunkelflaute* helps to further specify this vulnerability. It refers to a prolonged period during which renewable generation remains very low due to a lack of both wind and sunlight. Beck-Bang, Overgaard, and Keles show that this phenomenon poses a growing challenge for electricity systems in North-Western Europe, especially as conventional flexible capacities are simultaneously declining. In their prospective study covering eleven European countries by 2035, the authors show that periods of *dunkelflaute* may lead to situations in which part of electricity demand cannot be served, despite the existence of interconnections.

These episodes suggest that adequacy risk is no longer limited solely to traditional demand peaks. It may also result from the combination of high residual demand and simultaneously low renewable availability. Storage, demand-side response, and interconnections contribute to reducing this risk, but their ability to compensate for prolonged deficits remains limited when low renewable generation is widespread across the region (Elia, 2024).

2.1.3 Structural constraints of electricity systems

These developments must be understood in light of the physical constraints that are specific to electricity. Electricity remains difficult to store on a large scale and over long durations, which requires a quasi-permanent adjustment between production and consumption. At every moment, supply and demand must remain balanced in order to ensure the proper functioning of the electricity system. A significant imbalance may lead to corrective measures or even power outages.

This constraint becomes more difficult to manage as the share of variable renewable energy increases. The growing integration of wind and solar power increases production fluctuations and therefore reinforces the system's flexibility needs: dispatchable backup capacities, fast reserves, storage, and demand-side response (Liebensteiner & Wrienz, 2020; Beck-Bang et al., 2026). Situations such as nights without sunlight or periods of low wind require other resources to take over, while also accounting for the risk of unexpected outages affecting certain dispatchable capacities.

Security of supply also depends on the robustness of the network. Transmission constraints limit the ability to deliver electricity where it is needed. In this respect, the N-1 criterion remains fundamental: the network must be able to continue supplying electricity even in the event of the failure of a major component, thanks to redundancies and the meshed design of the system (Kyon Energy, 2026). Adequacy therefore has both a temporal and a spatial dimension: it is not sufficient for energy to be available somewhere within the system; it must also be capable of being mobilised and delivered at the critical moment.

These constraints explain why the energy transition does not merely raise the question of installed capacity volume. It also transforms the effective availability, flexibility, and delivery conditions of resources, thereby making a more refined assessment of adequacy necessary.

2.1.4 Measuring adequacy: reliable capacities and probabilistic indicators

2.1.4.1 Installed capacity, available capacity and de-rated capacity

The assessment of adequacy therefore first relies on a fundamental distinction between installed capacity and actually available capacity. Installed capacity corresponds to the sum of the nominal capacities of generation units, but the capacity effectively available at a given moment is lower, since outages due to maintenance or failures, as well as the intrinsic variability of certain technologies, must be taken into account.

Adequacy assessments therefore rely on so-called de-rated or reliable capacity, which applies availability factors to installed capacities (Newbery, 2020). Larsen and van Ackere point out in this regard that nominal capacity is converted into de-rated capacity using reliability factors, with highly contrasted orders of magnitude: around 0–5% for photovoltaics, 15–20% for wind power, and 79–92% for hydropower. These differences illustrate that installed capacity alone provides only limited information regarding adequacy.

The Belgian case particularly illustrates this phenomenon. The provided documents indicate that installed capacity in Belgium exceeds 29 GW, whereas peak winter demand averages around 12 to 14 GW, with 12.55 GW recorded in 2023 (FEBEG, 2026). At first sight, the margin therefore appears comfortable. However, this “paradox” is explained by the fluctuating availability of technologies, technical outages, and the intermittency of solar and wind power. A simple comparison between installed capacity and peak demand is therefore insufficient to conclude that there is no adequacy risk.

2.1.4.2 Adequacy indicators: *LOLE*, *EENS*, and *VoLL*

Since installed capacity alone provides only limited information regarding system reliability, adequacy assessments generally rely on probabilistic approaches that evaluate the likelihood and consequences of supply shortages.

Indicators such as Loss of Load Expectation (*LOLE*) estimate the expected number of hours during which available resources are insufficient to meet demand, while Expected Energy Not Served (*EENS*) captures the expected volume of energy that would not be supplied per year. *EENS* therefore complements *LOLE* by capturing the severity of shortage episodes: two systems may display the same *LOLE* but very different *EENS* values depending on the magnitude of deficits during critical hours. At the European level, *EENS* has indeed become a central indicator in adequacy assessments and reliability standards (Emissions-EUETS.com, 2025c; Kapeller et al., 2026; ENTSO-E, 2024; Emissions-EUETS.com, 2025a).

In addition, Value of Lost Load (*VoLL*) provides an economic benchmark by representing the economic value attributed by consumers to unsupplied electricity. More precisely, it corresponds to the maximum amount consumers would be willing to pay to avoid an interruption.

These indicators therefore illustrate that adequacy is not assessed through a binary distinction between shortage and security of supply, but rather through probabilistic and economic evaluations of reliability risk. In this perspective, a non-zero level of adequacy risk may be considered acceptable if eliminating shortages entirely would require disproportionately costly investments (Kapeller et al., 2026).

2.1.5 The Belgian case: an interconnected but vulnerable system

Belgium is characterised by a particularly strict reliability standard. The documents indicate that the LOLE cannot legally exceed 3 hours under normal winter conditions and 20 hours in the event of a severe winter (ENTSO-E, 2024; FEBEG, 2026). This requirement places Belgium among the strictest European countries in terms of security of supply.

At the same time, Belgium is highly integrated into the regional electricity market. It benefits from significant interconnections with neighbouring countries and can theoretically import up to 7.5 GW, representing more than half of its peak demand (FEBEG, 2026; ENTSO-E, 2024). This regional openness constitutes a major advantage, but it does not automatically guarantee the availability of surplus generation abroad. Cross-border flows may be reduced by technical constraints, market conditions, or widespread stress episodes, for example in the case of *loop flows*¹ or when neighbouring countries themselves face increased domestic demand during cold periods.

This tension between regional integration and external dependence is explained in the analysis by Larsen and van Ackere. The authors show that two options coexist in Europe: either a country seeks to cover its needs independently, at the cost of redundant and expensive investments, or it relies on cross-border exchanges, which requires close coordination, a high level of political trust, and credible assumptions regarding the future availability of capacities in neighbouring countries.

In the Belgian case, Elia had already estimated that, in addition to the development of intermittent renewable energy sources, significant thermal investments were required, amounting to approximately 3.6 GW by 2025, and that even under this scenario Belgium would remain highly dependent on imports during periods of high demand and low wind and solar generation (Larsen & van Ackere, 2023). Other analyses by Elia, cited by the European Commission, confirm this diagnosis by indicating an additional capacity need of around 2 GW by 2025, potentially reaching nearly 3.9 GW by 2032, in order to guarantee security of supply in Belgium (European Commission, 2022).

2.1.6 Section conclusion

Ultimately, security of supply cannot be reduced to a simple question of installed capacity. Adequacy depends on the actual availability of resources, their flexibility, as well as the ability of the network and interconnections to respond to critical situations.

The European energy transition complicates this assessment due to the development of variable renewable energy sources, the gradual phase-out of dispatchable capacities, and the uncertainty surrounding cross-border exchanges. Probabilistic indicators such as LOLE, EENS, and VoLL help formalise adequacy risks and support the assessment of economically acceptable levels of reliability.

In this context, the Belgian case particularly illustrates the tensions between the transformation of the electricity mix, regional dependence, and the maintenance of a high level of security of supply.

¹Loop flows are unplanned electricity flows transiting through the Belgian grid due to constraints on neighbouring networks.

2.2 The electricity market: functioning of the energy-only model and main limitations

2.2.1 A reference model in the organisation of the european electricity market

The so-called *energy-only* market constitutes the reference framework for the organisation of electricity markets in Europe, including in Belgium. Under this model, producers are remunerated solely through the sale of the electricity they generate, without any separate payment for installed capacity. The functioning of the market relies on several complementary time horizons. The *day-ahead* market, in which market participants trade electricity for the following day, plays a central role in wholesale price formation. It is complemented by the *intraday* market, which allows participants to adjust their positions during the same day according to forecasting deviations, as well as by the balancing market, managed by the transmission system operator in order to maintain, in real time, the balance between supply and demand (Papavasiliou et al., 2023; Papavasiliou, 2020).

This model is based on a fundamental idea: the market price should constitute the main economic signal, both to coordinate short-term production and to guide long-term investment decisions. In theory, a properly designed energy-only market can therefore stimulate the investments necessary to ensure security of supply, provided that prices correctly reflect supply, demand, and scarcity conditions (Mou et al., 2023; Newbery, D., 2020).

2.2.2 Price formation: merit order and uniform marginal pricing

The functioning of the day-ahead market is based on an auction system in which producers submit sales offers while buyers express their demand. The aggregation of offers forms a supply curve ranked according to increasing marginal costs, referred to as the *merit order*. Technologies with the lowest marginal costs, such as wind, solar, or nuclear power, are dispatched first, whereas more expensive thermal power plants, particularly gas-fired units, are activated last in order to meet demand.

The equilibrium price is determined by the most expensive production unit required to satisfy demand. This is the principle of **uniform marginal pricing**, or *pay-as-cleared* pricing. All producers therefore receive the same market price, regardless of their own production costs. When gas-fired power plants set the marginal unit, an increase in gas prices is directly transmitted to electricity prices (Papavasiliou et al., 2023). The sharp price increases observed in Europe from the second half of 2021 onwards were largely attributed to this dependence of electricity prices on the marginal cost of gas-fired power plants (CREG, 2022).

The following figure provides a simplified and illustrative representation of the Belgian merit-order structure. It is adapted from Elia's didactic illustration, with generation technologies adjusted to better reflect the current Belgian electricity mix.²

²Figure adapted from Elia (2025), *Adequacy & Flexibility Study for Belgium 2026–2036*, Figure A-1. Segment widths are illustrative and do not correspond to exact installed capacities. Several components of the real electricity system, including storage, interconnections, demand-side flexibility, strategic reserves and balancing mechanisms, are intentionally omitted for simplicity.

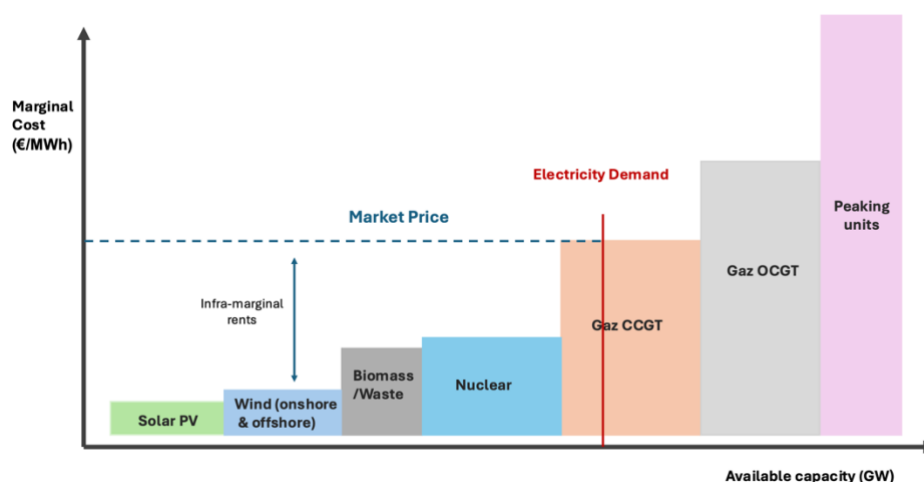


Figure 2.1. Simplified illustration of the Belgian merit-order structure

This mechanism performs a dual function. In the short term, it ensures an efficient allocation of generation resources. In the long term, it generates infra-marginal rents for producers whose costs are lower than the market price. These revenues therefore correspond to the difference between the price received and the production cost. They are essential within the energy-only model because they allow to cover fixed costs and investment expenditures associated with generation capacities.

The model therefore relies on the logic of *peak-load pricing*. Revenues earned during normal periods mainly cover variable costs, whereas episodes of high prices during peak periods allow to finance the remaining fixed costs. In this framework, *scarcity pricing* plays a central role: when available capacity becomes scarce, prices must be allowed to increase significantly in order to provide a sufficient investment signal (Newbery, 2020).

However, it is important to note that this mechanism may also lead to controversial effects, such as excessively high infra-marginal rents, particularly during periods of strong fuel price increases. Producers with low marginal costs may then earn substantial profits (*windfall profits*), even without any increase in their production costs. This phenomenon notably gave rise to major debates in Europe during the 2021-2022 energy crisis.

2.2.3 Transformation of the market through the energy transition

The growing integration of renewable energy sources is profoundly transforming the functioning of the energy-only market. Renewable technologies have very low marginal costs, exerting downward pressure on average market prices. However, they are also intermittent and uncertain, thereby increasing the need for flexibility, reserves, and real-time balancing adjustments (Papavasiliou et al., 2023; Papavasiliou, 2020).

This evolution is gradually modifying the nature of scarcity in electricity markets. In a system dominated by dispatchable generation resources, scarcity primarily concerned the availability of energy. With the development of variable renewable energy sources, the economic value of the system increasingly shifts towards resources capable of maintaining the real-time balance of the network, such as flexible power plants, storage, or demand response.

However, the current design of European electricity markets imperfectly values these services. The different reserve products are traded on specific platforms, notably PICASSO for aFRR and MARI for mFRR, without genuine co-optimisation with the energy market (Papavasiliou & Avila, 2024; Roumkos et al., 2022). This separation limits the market's ability to fully reflect

the economic value of available reserves. A system may therefore not face an energy shortage in the strict sense while still having insufficient reserve capacities. In such situations, electricity market prices do not adequately reflect the economic value of the remaining reserve capacities required to ensure system security.

In order to better value this scarcity, some contributions propose the introduction of mechanisms such as *Operating Reserve Demand Curves* (ORDC), which explicitly add a scarcity premium when reserve levels decline (Newbery, 2020). The objective is to generate price signals that are more frequent and less abrupt than those produced solely during extreme scarcity events.

2.2.4 Limitations of the energy-only model

In theory, the energy-only market should therefore be capable of ensuring system adequacy through scarcity price signals. In practice, however, several limitations prevent these signals from fulfilling their role. These include the low short-term elasticity of demand, the existence of price caps, the insufficient valuation of reserves and flexibility, the high volatility of market revenues, and the absence of financial hedging mechanisms suitable for long-term investment horizons.

These different limitations call into question the ability of this model, on its own, to guarantee a sufficient level of investment to ensure security of supply. This issue is generally referred to in the literature as the *missing money problem*.

2.3 The missing money problem

2.3.1 Definition and economic logic

The revenues generated during scarcity episodes and through infra-marginal rents. In practice, however, price signals do not always ensure to guarantee sufficient remuneration for the capacities required to ensure security of supply.

The missing money therefore refers to the gap between the revenues actually earned on the market and the level of revenues necessary to cover the fixed costs and investment costs of generation capacities (Lindell, 2025).

2.3.2 Economic origins of the missing money problem

2.3.2.1 Constrained and incomplete price formation

One of the main causes of the *missing money problem* lies in the existence of *price caps* and other regulatory constraints. Often introduced for reasons related to consumer protection or the control of market power, these limitations prevent prices from reaching their theoretical level during scarcity situations, thereby reducing the potential revenues of producers (Schittekatte & Meeus, 2021; Percebois & Pommeret, 2022).

Consistently, the literature shows that the revenues earned by peaking power plants remain insufficient to cover their investment costs in an environment where prices are capped.

2.3.2.2 The absence of complete markets (missing markets)

Beyond the *missing money* problem, the literature also highlights the existence of *missing markets*, particularly regarding long-term risk hedging.

Forward markets and over-the-counter contracts allow hedging part of short- or medium-term price variations, but their time horizon generally remains limited compared to the economic

lifetime of investments in generation or flexibility resources (European Commission, 2022; Schittekatte & Meeus, 2021). This limitation is particularly important in a sector characterised by significant uncertainty regarding future electricity, gas, and carbon prices, as well as the evolution of energy policies. Consequently, investors remain exposed to a mismatch between fixed costs incurred over the long term and uncertain market revenues, often dependent on rare episodes of high prices. This absence of sufficient hedging may increase the cost of capital and reduce incentives to invest in the capacities required to ensure security of supply (Newbery, 2020).

2.3.2.3 Weak demand responsiveness and poor valuation of scarcity

Another fundamental limitation lies in the low elasticity of demand. Consumers react only weakly to short-term price variations, which prevents the market from correctly reflecting the value of scarcity (Schittekatte & Meeus, 2021).

2.3.2.4 Security of supply as a public good

Finally, these remuneration deficiencies are also explained by the economic nature of security of supply. It presents certain characteristics of a public good, insofar as it benefits all consumers without the possibility to individually exclude those who do not contribute to it.

In this context, producers do not have optimal incentives to invest in additional capacities because they cannot capture the full social value of these investments (European Commission, 2022). This externality leads to structural underinvestment within a purely market-based framework.

2.3.3 Consequences for investment and security of supply

The missing money problem concretely results in underinvestment in the capacities required to ensure security of supply, particularly flexible resources. This leads to a situation in which certain existing capacities become unprofitable, while new capacities are not built.

2.3.4 The belgian case: a materialisation of the missing money problem

Belgium constitutes a particularly revealing example of this phenomenon. The gradual nuclear phase-out between 2022 and 2025 leads to a significant reduction in available dispatchable capacity, creating a structural need for new capacities. Adequacy assessments show that, in the absence of intervention, the level of shortage risk would largely exceed the national reliability standard, with a *Loss of Load Expectation* potentially exceeding 10 hours, compared with a target of 3 hours (European Commission, 2022).

Furthermore, the Belgian authorities estimate that only a fraction of the required new capacities would be installed if relying solely on revenues generated by the energy-only market (Vandorpe, 2022). This situation directly illustrates the effects of these remuneration deficiencies on investment decisions.

2.4 Introduction to capacity remuneration mechanisms

2.4.1 Mechanisms designed to address an adequacy problem

Capacity remuneration mechanisms (CRMs) are arrangements that remunerate capacity providers not only for the electricity effectively produced, but also for their potential availability to supply electricity when the system requires it.

As highlighted in the previous section, electricity markets based on an energy-only model may present limitations in terms of investment signals, particularly due to the missing money

problem. In this context, CRMs have progressively been introduced in order to complement revenues generated by the energy market and to guarantee a sufficient level of capacity to ensure security of supply (European Commission, 2022).

CRMs therefore aim to provide an additional investment signal by remunerating the availability of capacities rather than electricity production alone. They help to stabilise producers' revenues and to reduce the risks associated with investments in capacities that are used infrequently but remain essential during periods of system stress (Lindell, 2025; Simoglou & Biskas, 2023).

Beyond the missing money problem, several studies emphasise that security of supply has a collective dimension and constitutes an objective defined by public authorities through reliability standards. From this perspective, CRMs operate at the intersection between market logic and public intervention: they seek to preserve the competitive functioning of the market while correcting its shortcomings regarding adequacy.

2.4.2 The main types of capacity mechanisms in Europe

Capacity mechanisms take various forms across Europe. This diversity can nevertheless be grouped into two broad analytical categories. The literature distinguishes between so-called *market-wide* mechanisms, which cover the entire electricity system and aim to ensure overall adequacy, and *targeted* mechanisms, which correspond to more specific interventions designed to address a particular or temporary need (Lindell, 2025). *Market-wide* mechanisms notably include centralised capacity markets and decentralised obligation-based mechanisms, in which all eligible resources may participate. By contrast, *targeted* mechanisms include arrangements such as strategic reserves, targeted tenders for new capacities, or certain capacity payments, which generally focus on specific technologies, capacities, or situations.

There is therefore no single CRM model, but rather several possible architectures depending on national preferences, the electricity mix, the regulatory framework, and the nature of the adequacy risk. Among these mechanisms, capacity markets and strategic reserves currently appear as the two most visible forms within the European Union. In a central buyer capacity market, a designated authority, generally the transmission system operator or another designated entity, determines the required capacity volume and organises an auction in order to select the necessary resources. This type of mechanism transforms capacity into a distinct product separate from the electricity produced, thereby creating an additional source of revenue for selected participants (Simoglou & Biskas, 2023). By contrast, in a decentralised mechanism, such as the French model based on capacity certificates, the coverage obligation falls more directly on suppliers or other market participants, who must acquire the required certificates, notably from producers to whom such certificates have been allocated, in order to guarantee that sufficient capacity is available during peak periods (Lindell, 2025).

The strategic reserve follows a different logic. In this case, certain capacities are maintained outside the energy market and are activated only as a last resort, when the market is no longer able to balance supply and demand. This mechanism is often considered less intrusive for the short-term market, since the reserved capacities do not normally participate in wholesale markets. However, it is also frequently regarded as less suitable for triggering significant investments in new capacities, because it acts more as a safety net than as a broad and durable investment signal (Simoglou & Biskas, 2023).

The different mechanisms also differ in terms of the nature of the product exchanged. In several countries, the mechanism takes the form of a simple availability obligation, in which producers

are remunerated for being available when the system requires it, while retaining the entirety of the revenues generated by the energy market. In others, notably in Belgium, Ireland, and Italy, the product is based on *reliability options* (Mastropietro et al., 2024). This distinction is essential because it influences the way in which the mechanism interacts with the energy market and contributes to limiting excessive rents during periods of strong system stress.

2.4.3 Reliability options: an articulation between capacity and the energy market

Reliability options constitute a particular form of capacity product. Under this scheme, the capacity provider selected through the auction receives a fixed capacity premium, but commits in return to reimbursing part of its revenues when the reference market price exceeds a certain threshold, known as the *strike price*. Concretely, when this reference price exceeds the *strike price*, the provider must repay the difference calculated on the basis of the contracted capacity. This mechanism pursues a dual objective: on the one hand, it reduces producers' revenue uncertainty by providing them with stable remuneration; on the other hand, it limits the exceptional rents that could otherwise be captured during periods of strong scarcity.

The interest of reliability options lies in the fact that they allow to address market failures related to adequacy to be addressed while limiting interference with the normal functioning of the energy market. They do not eliminate the scarcity signal, since market prices may still increase during periods of stress; however, they organise a repayment mechanism that limits the accumulation of capacity remuneration and very high scarcity rents (Simoglou & Biskas, 2023; Mastropietro et al., 2024). From this perspective, reliability options are often presented as a solution seeking to reconcile two objectives: guaranteeing sufficiently predictable revenues to support investment while preserving as much as possible the informational role of the short-term market.

It should nevertheless be emphasised that reliability options do not constitute a uniform mechanism. Their design may vary significantly across countries: choice of the reference price, method used to determine the *strike price*, penalty regime in the event of non-availability, or limits placed on the financial losses borne by contract holders. The Belgian case is particularly interesting in this regard, as recent adjustments have introduced exemptions from repayment obligations for certain technologies, notably demand response and storage, in order to avoid competitive disadvantages and support their development (Timera Energy, 2025). This evolution illustrates the intention to make reliability options the foundation of a mechanism that is simultaneously adequacy-oriented, technologically open, and regulated so as to limit excessive profits.

2.4.4 The Belgian CRM: general logic and justification

The Belgian CRM was introduced in response to an anticipated adequacy problem from 2025 onwards, mainly linked to the nuclear phase-out between 2022 and 2025, combined with the gradual retirement of certain thermal capacities in Belgium and neighbouring countries (European Commission, 2022; Boisseleau, 2021). The European Commission explicitly notes that the Belgian authorities considered that they would face a security of supply problem from 2025 onwards and that the sole functioning of the energy market would not ensure the emergence of sufficient capacities to guarantee timely security of supply.

In this context, the CRM was not designed as a simple sectoral support mechanism, but as an instrument aimed at guaranteeing a capacity volume consistent with the reliability standard adopted by Belgium, set at a *Loss of Load Expectation* of three hours per year. The mechanism therefore follows a probabilistic adequacy logic: it does not aim to eliminate all risk of shortage,

but rather to maintain it at a level considered acceptable by public authorities (European Commission, 2022).

2.4.5 Practical organisation of the Belgian mechanism

The Belgian CRM is a central buyer capacity market mechanism organised around auctions. The European Commission classifies it as both *market-wide* and *technology-neutral*.

The general framework of the mechanism is defined by the Belgian public authorities, which notably establish the operating rules, the timetable, and the volumes to be secured, in accordance with the applicable European framework. The operational organisation is entrusted to Elia, the Belgian transmission system operator, which is responsible for the practical implementation of the auctions and for carrying out adequacy studies in order to assess the future needs of the electricity system. In parallel, the Commission for Electricity and Gas Regulation (CREG), as the federal regulator, performs a role of supervision, evaluation, and advisory support, notably by ensuring the proper functioning of the mechanism and the maintenance of adequate competitive conditions (European Commission, 2022; SPF Économie, n.d.).

The process first relies on a prequalification phase intended to verify which capacities are eligible to participate. Subsequently, the selected capacities are chosen through a competitive procedure. The mechanism is open both to existing and new capacities, as well as to storage and demand-side management. It also allows the aggregation of several resources so that they may participate collectively in the mechanism, including when these resources rely on different technologies. This openness constitutes an important feature of the Belgian design: it aims to prevent the mechanism from being reserved for a particular technology and to allow a broad range of resources to contribute to adequacy (European Commission, 2022; SPF Économie, n.d.).

The timetable of the Belgian CRM mainly relies on an auction organised four years before the delivery year ($Y-4$), complemented by auctions organised closer to real time, notably $Y-2$ and $Y-1$ auctions. This architecture serves to combine two objectives. On the one hand, it gives sufficient time to projects requiring longer development periods, such as certain new power plants or major investments. On the other hand, it provides the possibility to adjust, closer to the delivery year, the volume to be secured based on updated information regarding demand, the existing generation fleet, and the evolution of the system. The official Belgian documentation indeed emphasises that this dual structure makes it possible to reconcile technologies requiring long preparation periods with more rapidly deployable resources, such as certain forms of demand-side management (European Commission, 2022; SPF Économie, n.d.; Elia, n.d.).

The auctioned volume is not determined arbitrarily. It is established on the basis of adequacy studies and the reliability standard adopted by Belgium. The general logic therefore remains centralised: public authorities define the overall capacity requirement to be covered, while the market reveals, through auctions, which resources are capable of satisfying this requirement and at what price.

2.4.6 Financing, remuneration, and associated obligations

Selected capacities receive remuneration for their availability during the delivery year. For the first auctions, Belgium adopted a *pay-as-bid* pricing rule, meaning that each selected participant receives the price it offered. Although a transition towards a *pay-as-clear* system had been

considered for subsequent auctions, Belgian CRM auctions continue, to this day, to operate according to a *pay-as-bid* logic. This choice was notably motivated by concerns that the first auctions, in the context of strong cost heterogeneity, could generate excessively high infra-marginal rents if a uniform pricing rule were immediately applied.

The mechanism also provides for differentiated contract durations. While the standard contract length is a one-year, capacities requiring substantial investment may secure longer contracts, extending up to 3, 8, or 15 delivery years depending on the case. The aim is to better accommodate the financing needs of capital-intensive projects while preserving the competitive structure of the mechanism (European Commission, 2022; SPF Économie, n.d.).

2.4.7 The economic logic of the Belgian model

The Belgian CRM represents a compromise between security of supply, competitive principles, and rents regulation. On the one hand, the mechanism seeks to attract the required investments and retain capacities useful to the system. On the other hand, it attempts to do so through a competitive, technology-neutral process based on an assessment of the resources' expected contribution to adequacy. Thus, resources are remunerated not according to their gross nominal capacity, but according to their "reliable" or de-rated capacity, to better reflect their expected contribution to security of supply (European Commission, 2022).

The use of reliability options reinforces this approach. The objective is both to limit exceptional profits and to incentivise contracted units to remain available when security of supply is genuinely at stake. In this sense, the Belgian CRM does not aim to replace the energy market, but rather to complement it where the latter falls short of ensuring a level of adequacy consistent with public objectives.

3. Literature Review

The previous section established the conceptual institutional and market foundations necessary to understand the functioning and rationale of capacity remuneration mechanisms. Building on this framework, the following section focuses more explicitly on the academic debates and criticisms surrounding these mechanisms.

3.1 Criticisms of capacity remuneration mechanisms

3.1.1 Useful instruments, but with contested economic efficiency

Although capacity remuneration mechanisms are generally presented as instruments capable of improving system adequacy, their economic efficiency is recurrently questioned in the literature.

The practical implementation of these mechanisms is often criticised for its economic inefficiency and its tendency to lead to situations of capacity *over-procurement*. From the consumers' perspective, the reduction in spot prices linked to the increase in available capacity does not necessarily compensate for the capacity payments granted to producers, meaning that consumers ultimately finance the mechanism (Lindell, 2025). A comparison between targeted mechanisms and market-wide mechanisms further shows that the latter are associated with greater institutional and regulatory complexity (Holmberg et al., 2025).

3.1.2 A risk of over-procurement and poor calibration

Another important criticism lies in the fact that CRMs rely on administrative parameters whose determination is particularly delicate. Estimating the “reliable” capacity of resources with very different profiles (notably variable renewable energy sources, whose production depends on weather conditions, or demand response, whose availability depends on consumer behaviour) strongly depends on the assumptions adopted by the regulator. In practice, authorities may be incentivised to prioritise security of supply in their estimations, which can lead to excessive procurement of capacity. (Lindell, 2025).

At the European level, poorly coordinated national mechanisms may also lead to overinvestment situations, particularly when capacity needs are determined on the basis of national scenarios that are inconsistent with one another. In such cases, the CRM risks financing excessive capacity, or capacities located inappropriately, thereby weakening the overall efficiency of the European electricity system (Holmberg et al., 2025).

3.1.3 Competition distortions and problematic cross-border effects

Beyond calibration and cost issues, capacity mechanisms also raise concerns regarding competition and the integration of the European electricity market.

In theory, foreign capacities should be able to contribute to the security of supply of another Member State through European interconnections. In practice, however, Member States implement national mechanisms according to different rules, which may reduce visibility for investors, limit competition between market participants, and weaken the expected benefits of European market integration. This lack of coordination between countries therefore tends to hinder cross-border participation, particularly when access costs to interconnections are high or when the availability of exchanges during periods of system stress remains uncertain (Holmberg et al., 2025).

The Belgian case concretely illustrates these issues. In its decision to open proceedings concerning the Belgian CRM, the European Commission raised several concerns regarding the compatibility of the mechanism with European requirements related to competition and openness to foreign participation. In particular, it considered that the absence of multi-year contracts for indirect foreign capacities, combined with the application of an *intermediate price cap*, risked preventing these capacities from offering prices that genuinely reflected their costs and, consequently, discouraging their participation in the mechanism (European Commission, 2022).

3.1.4 A heavy and complex regulatory architecture

Capacity markets are often regarded in the literature as excessively complex, to the point that regulators as well as market participants may not possess sufficient resources to make fully informed decisions. This increases risk aversion, generates inefficiencies, and may even discourage certain small producers from participating (Lindell, 2025).

This complexity appears particularly clearly in mechanisms based on *reliability options*. These instruments have the advantage of limiting interference with the energy market, but they in fact encompass a wide range of design choices (reference market, strike price, penalty regime, fixed commitment or *load-following* commitment) that must be adapted to the electricity system concerned (Mastropietro et al., 2024). In other words, even though products such as reliability options are often presented as relatively elegant solutions, their implementation relies on a set

of technical and regulatory parameters whose poor calibration may reduce the effectiveness of the mechanism.

The Belgian example illustrates the calibration difficulties associated with this type of mechanism. It combines numerous elements (reliability options, strike prices, Y-4 and Y-1 auctions, penalties, etc.). This diversity reinforces the influence of regulatory choices on the mechanism's outcomes, thereby raising issues related to transparency and competitive neutrality.

3.1.5 Support mechanisms that may conflict with energy transition objectives

A central line of criticism concerns the articulation between CRMs and the energy transition. Recent literature emphasises that several European member states continue to operate under a contradictory *policy mix* (Kozlova et al., 2023). On the one hand, support schemes for renewable energy pursue decarbonisation objectives; on the other hand, capacity mechanisms often support fossil-fuel-based resources intended to compensate for the intermittency of renewables, which may slow down the energy transition. Even when renewable technologies are allowed to participate in capacity mechanisms, their capacity is often *de-rated*, which significantly reduces the revenues they can obtain from these mechanisms and thereby limits their incentive to contribute to system reliability through this channel (Kozlova et al., 2023).

Insofar as CRMs primarily aim to ensure security of supply, remuneration therefore tends to concentrate on resources considered the most stable, such as certain dispatchable thermal power plants, particularly gas-fired units. This priority given to flexibility may come into tension with climate objectives and emission reduction policies, even though emission limits have been introduced at the European level in order to restrict this effect (Lindell, 2025).

However, this same logic may also support the development of storage and demand response, illustrating that the effects of CRMs depend very strongly on their specific design.

3.1.6 CRMs do not solve all the weaknesses of market design

Finally, several studies emphasise that a CRM should not be considered a perfect or self-sufficient solution. The debate opposing *scarcity pricing* and capacity mechanisms is, to some extent, poorly framed. CRMs do not eliminate market imperfections, but rather partially shift them into the regulatory sphere (Papavasiliou et al., 2023; Papavasiliou, 2020).

Their introduction does not remove the need to improve the functioning of the energy market itself. It remains necessary to better value flexibility, reserves, demand response, and cross-border participation before, or at least in parallel with, the implementation of capacity mechanisms. From this perspective, the CRM appears less as a definitive solution than as a corrective instrument, potentially necessary, but imperfect and costly, which must remain closely articulated with other *market design* reforms.

3.2 Research gap and contribution

The literature on capacity remuneration mechanisms has extensively focused on their ability to address adequacy concerns and compensate for some limitations of energy-only markets, particularly those related to the missing money problem and long-term investment incentives. At the same time, a substantial part of the literature has highlighted several criticisms associated with CRMs, including risks of inefficient calibration, over-procurement, distorted investment incentives, regulatory complexity, and tensions with European market integration.

However, comparatively less attention has been devoted to the concrete financial implications of reliability-option-based mechanisms once both capacity remuneration and repayment obligations associated with reliability options are considered jointly. While reliability options are often presented as instruments capable of limiting excessive scarcity rents and improving market discipline, the literature provides limited quantitative discussion regarding how repayment obligations may affect the effective remuneration retained from CRM contracts under different future electricity market conditions.

This question is particularly relevant in a context where repayment obligations directly depend on future electricity prices and may therefore vary significantly depending on market conditions, scarcity episodes, renewable penetration, and system stress situations. As a result, the share of CRM remuneration effectively retained after reliability option repayments remains uncertain at the moment capacity contracts are awarded.

4. Methodology

4.1 Overall methodological approach

4.1.1 Research Objective

The objective of this thesis is to evaluate one dimension of the financial implications of the Belgian Capacity Remuneration Mechanism (CRM) by estimating the expected payment gap associated with reliability options.

In the Belgian CRM, capacity providers receive a fixed remuneration in exchange for availability commitments but may also be required to make repayments when electricity prices exceed a predefined strike price. Assessing the financial outcomes associated with this remuneration structure therefore requires considering both capacity remuneration and expected future repayments.

In this thesis, the payment gap refers to the difference between the capacity remuneration received by contracted providers through the Belgian CRM and the expected repayments generated by reliability options under future electricity market conditions.

The objective of this thesis is therefore to estimate how the expected balance between capacity remuneration and reliability option repayments may evolve under alternative future electricity market conditions and to explore what this balance may imply for the level of remuneration effectively retained from the CRM by capacity providers, as well as for the interpretation of the role of the CRM within the scope of this study.

The analysis focuses on one specific financial dimension of the Belgian CRM and does not aim to provide a complete assessment of the overall economic efficiency of the mechanism.

4.1.2 Conceptual definition of the payment gap

Conceptually, the expected payment gap can be represented as follows³:

³ In this thesis, the term *payment gap* is introduced for analytical convenience and is not intended to represent a standard metric in the CRM literature.

$$E[GAP] = BP - E[RO^s] \quad (4.1)$$

where:

- BP = bid-volume weighted average accepted bid price for the Belgian CRM Y-4 auction for the 2029–2030 delivery period (27.333,51 k€/MW/year)⁴
- $E[RO_s]$ = expected reliability option repayment under scenario s

4.1.3 Why simulation is required

Estimating reliability option repayments requires assumptions regarding future electricity prices. The value of the reliability option repayment (RO) is computed for each simulated price trajectory. In the Belgian CRM framework, the reliability option payback obligation is triggered whenever the reference energy spot price, defined by Elia as the day-ahead price, exceeds the strike price (Elia, n.d.). Accordingly, reliability option repayments are calculated as follows:

$$RO^s = \sum_{t=1}^T \max(P_t^s - K, 0) \times \Delta t \quad (4.2)$$

where:

- $K = 319$ denotes the strike price (expressed in €/MWh).⁵
- Δt represents the time step duration (1 hour).
- $T = 8760$, is the number of simulated hours.

Since future prices are uncertain, a Monte Carlo simulation approach is used to generate multiple plausible future price realizations. For each simulated price trajectory, reliability option repayments are computed, generating a distribution of possible repayment outcomes.

The expected reliability option repayment is then estimated as the average repayment across all simulated trajectories:

$$E[RO] \approx \frac{1}{N} \sum_{s=1}^N RO^s \quad (4.3)$$

where:

- RO^s = reimbursement obtained in simulation s
- N = total number of trajectories (1,000)

Equation (4.2) defines the total reliability option repayment associated with a simulated price trajectory, while Equation (4.3) estimates the expected repayment across all simulated trajectories

The realism of the simulated repayment outcomes therefore depends on the ability of the price model to reproduce key characteristics of electricity markets. Rather than generating electricity prices as independent observations drawn from a static distribution, this thesis models

⁴ The Belgian CRM applies a pay-as-bid clearing mechanism, meaning that each selected CMU receives its own bid price as capacity remuneration. Therefore, the bid-volume weighted average accepted bid price published by Elia is used as a proxy for annual CRM remuneration (Elia, 2025c).

⁵ 319 €/MWh is the strike price associated with the Y-4 auction for the 2030/2031 delivery period (Elia, 2025a)

electricity prices as a dynamic process incorporating persistence, seasonality and time-varying spike probabilities. In particular, the normal component of the price process follows an autoregressive structure, meaning that current price conditions partly depend on previous realizations.

The objective of this dynamic specification is not to isolate the individual effect of each model component on reliability option repayments, but to generate plausible future market conditions from which expected reliability option repayments and the associated payment gap can be estimated.

4.1.4 General methodological framework

The methodological approach adopted in this thesis consists of four main steps aiming to estimate the expected payment gap associated with reliability options under alternative electricity market scenarios for 2030.

Step 1: Specification and calibration of the electricity price process

In a first step, a reference electricity price process is specified and calibrated using historical market data. The objective is to define a baseline configuration that reproduces the main characteristics and dynamics observed over the historical period and serves as the basis for subsequent scenario adjustments and simulations.

Electricity prices are decomposed into a deterministic component, a regular stochastic component and a spike component in order to reproduce key characteristics of electricity markets. The deterministic component captures recurrent seasonal patterns, the regular stochastic component represents normal market fluctuations through an autoregressive structure, while the spike component accounts for extreme price events.

Step 2: Construction of alternative scenarios and parameter adjustment

In a second step, the calibrated baseline model is adjusted to reflect alternative assumptions regarding future electricity market conditions. Scenario-specific modifications are introduced to selected model parameters, including volatility, spike frequency, spike magnitude and the deterministic seasonal component.

Step 3: Monte Carlo simulation of future electricity price trajectories

The adjusted price process is then simulated within a Monte Carlo framework to generate a large number of plausible electricity price trajectories for each scenario.

Step 4: Reliability option valuation and payment gap estimation (Results)

Finally, reliability option repayments are computed for each simulated trajectory and averaged in order to be compared with the corresponding capacity remuneration. This allows estimating the expected payment gap under each scenario and evaluating how alternative market conditions may influence its magnitude.

4.1.5 Methodological positioning

This thesis does not aim to propose a new methodological framework.

Rather, it combines established approaches from electricity price modeling and simulation-based valuation in order to estimate the expected payment gap associated with reliability options under the Belgian CRM.

The contribution of this thesis therefore lies primarily in the application and integration of existing methodologies within the specific institutional context of the Belgian Capacity Remuneration Mechanism and alternative electricity market scenarios for 2030.

4.2 Data & electricity price modeling

Since reliability option repayments directly depend on future electricity prices, simulating future market conditions requires a model capable of reproducing the main characteristics of electricity price dynamics. This section introduces the decomposition framework adopted in this thesis and explains how each component is specified and calibrated.

4.2.1 Electricity price decomposition framework

To represent electricity price dynamics, this study adopts a decomposition framework that separates predictable seasonal patterns and stochastic fluctuations. This structure reflects the idea that electricity prices result from the combination of regular temporal patterns, normal market fluctuations and occasional extreme events.⁶

Formally, electricity prices are decomposed as follows:

$$P_t = \mu_t + X_t + J_t \quad (4.4)$$

where:

- μ_t = deterministic component,
- X_t = normal stochastic component,
- J_t = spike component.

This decomposition is implemented sequentially. First, deterministic patterns are estimated and removed from the historical price series to obtain a residual component. This residual component is then separated into a normal stochastic component and a spike component, which are modelled independently before being recombined to simulate future electricity prices.

4.2.2 Data collection & preparation

This study relies on historical Belgian day-ahead electricity prices covering the period 2016-2026, collected from the ENTSO-E Transparency Platform.

Since the original dataset contains observations at different temporal resolutions (hourly and 15-minute intervals depending on the period), all observations are converted to an hourly frequency to ensure consistency over the full sample. For periods with quarter-hourly observations, hourly prices are computed as the average of the four corresponding intervals.

Calendar variables (hour of day, day of week and month) are subsequently derived from the timestamp information in order to capture temporal patterns in electricity prices.

All data preparation, parameter calibration and Monte Carlo simulations were implemented in Python.

⁶ This representation is inspired by the electricity price modelling literature, which commonly distinguishes deterministic seasonal effects from stochastic price dynamics (Weron, 2006; Janczura and Weron, 2010). In addition, electricity prices are known to combine regular fluctuations with occasional spike events, motivating the separate treatment of regular stochastic fluctuations and extreme events (Huisman & Mahieu, 2003). In this study, the stochastic component is therefore further separated into a normal fluctuation component (X_t) and a spike component (J_t) for estimation and simulation purposes.

4.2.3 Historical electricity price characteristics

The historical electricity price series is examined in order to illustrate the main characteristics that the selected modeling framework aims to reproduce.

Table 4.1. Descriptive statistics of historical electricity prices

Statistic	Value
Number of observations	90072
Mean	80,98
Median	55,48
Standard deviation	82,01
Minimum	-500
Maximum	871
Skewness	2,86
Kurtosis	11,78

Source: author's calculations based on ENTSO-E data.

Table 4.1 presents the main descriptive statistics of historical electricity prices over the sample period. Several characteristics of the price series can be highlighted. First, the relatively high standard deviation (82 €/MWh) indicates substantial variability in electricity prices over time, suggesting the presence of an important stochastic component. In addition, the large range between the minimum (−500 €/MWh) and maximum (871 €/MWh) suggests the presence of occasional extreme market conditions that may not be adequately represented by regular price fluctuations alone. Finally, the elevated kurtosis (11.78), substantially above the level associated with a normal distribution (3), suggests the presence of heavier tails and indicates that large deviations from typical price levels play a more important role than would be expected under a normal distribution.

Overall, these characteristics illustrate the relevance of distinguishing between deterministic patterns, regular market fluctuations, and occasional extreme events. They therefore provide empirical support for the decomposition adopted in this study and inform the specification of each model component.

The following section details how each component of the decomposition framework is specified and estimated.

4.2.4 Electricity price component modeling

In order to later generate future electricity price trajectories within the Monte Carlo framework, each component of the electricity price decomposition introduced above is specified and calibrated using historical data.

4.2.4.1 Modeling of the deterministic component μ

The deterministic component captures the predictable seasonal structure of electricity prices. More specifically, it reflects systematic variations associated with the hour of the day, the day of the week, and the season of the year. In order to isolate stochastic fluctuations from these recurring patterns, the deterministic component is estimated separately from the residual process. This follows the sequential decomposition approach introduced previously.

The price is decomposed as:

$$P_t = \mu_t + R_t \quad (4.5)$$

Where P_t is the observed day-ahead electricity price at time t , μ_t is the deterministic component and R_t represents the residual stochastic component.⁷

Specification of the deterministic component

The deterministic component μ_t represents the expected level of electricity prices based solely on calendar effects. It is estimated using a linear regression model including dummy variables for the hour of the day, the day of the week, and the month of the year:

$$\mu_t = \alpha + \sum_{h=1}^{23} \beta_h H_{\{h,t\}} + \sum_{d=1}^6 \gamma_d D_{\{d,t\}} + \sum_{m=1}^{11} \delta_m M_{\{m,t\}} \quad (4.6)$$

where:

- α is a constant term,
- $H_{\{h,t\}}$ are hourly dummy variables,
- $D_{\{d,t\}}$ are day-of-week dummy variables,
- $M_{\{m,t\}}$ are monthly dummy variables,
- β_h , γ_d , and δ_m are the coefficients associated with each category.

Each dummy variable takes the value 1 if the observation belongs to the corresponding category (e.g., a given hour or month), and 0 otherwise.

This specification allows to capture the main deterministic patterns observed in electricity prices, such as intra-day, weekly and seasonal effects.⁸ The deterministic model is estimated using Ordinary Least Squares (OLS), which provides an empirical estimate of the average impact of calendar effects.⁹

The estimation yields a set of coefficients associated with each calendar dummy variable. Reporting all estimated coefficients in the main text would be cumbersome and difficult to interpret. Therefore, the complete regression output of the deterministic component estimation is reported in Appendix A, while the main results are illustrated graphically in order to highlight the most relevant temporal patterns in electricity prices.

Re-centering of the Deterministic Level

Descriptive statistics computed on the historical dataset show that the average electricity price reached approximately 245 €/MWh in 2022, compared with approximately 63 €/MWh across the remaining years of the sample (see Appendix B for detailed diagnostics). This observation

⁷ Inspired by the decomposition proposed by Janczura and Weron (2010) & Janczura et al. (2013), where electricity prices are represented as the sum of a deterministic seasonal component and a stochastic component ($P_t = f_t + X_t$).

⁸ This specification is inspired by Janczura et al. (2013), which emphasizes the importance of modeling deterministic calendar effects such as daily, weekly, and annual seasonality in electricity prices. The authors also discuss the use of dummy variables for capturing seasonal patterns, although they do not directly employ the same dummy-variable specification in their analysis.

⁹ Simonato and Denault (2015) estimate the deterministic seasonal component of electricity prices using seasonal dummy variables and an Ordinary Least Squares (OLS) procedure. The calendar-based specification adopted here extends this approach by incorporating additional intra-day and weekly effects.

indicates that 2022 differs from the remaining sample and may exert a disproportionate influence on the average level of the deterministic component used for simulation.

Since the objective of this study is not to reproduce the exceptional market conditions observed in 2022 but rather to simulate plausible electricity price trajectories for 2030, the deterministic component is adjusted through a re-centering of its mean level.¹⁰

The predicted deterministic component (μ_t) is shifted by a constant amount so that its average matches the average electricity price observed over a set of representative years (2016, 2017, 2018, 2019, 2020, 2021, 2023, 2024, 2025 and 2026), resulting in an adjusted component (μ_t^{adj}).

The adjustment is performed ex post on the predicted deterministic component and therefore does not modify the calendar coefficients estimated from the full historical sample, so the temporal structure obtained from this estimation is retained. Consequently, all observations, including those from 2022, continue to contribute to the estimation of hourly, weekly and monthly patterns, while the re-centering avoids a distortion of the overall price level used for simulation. Additional robustness checks on the sensitivity of estimated calendar effects to the inclusion of individual years are reported in Appendix C.

Interpretation

The resulting deterministic component captures the stable and predictable structure of electricity prices. It should be interpreted as the expected price level in the absence of stochastic fluctuations, while deviations from this component are captured in the residual process.

The figure below illustrates the observed prices for January 2021 and the adjusted deterministic component for a representative period.

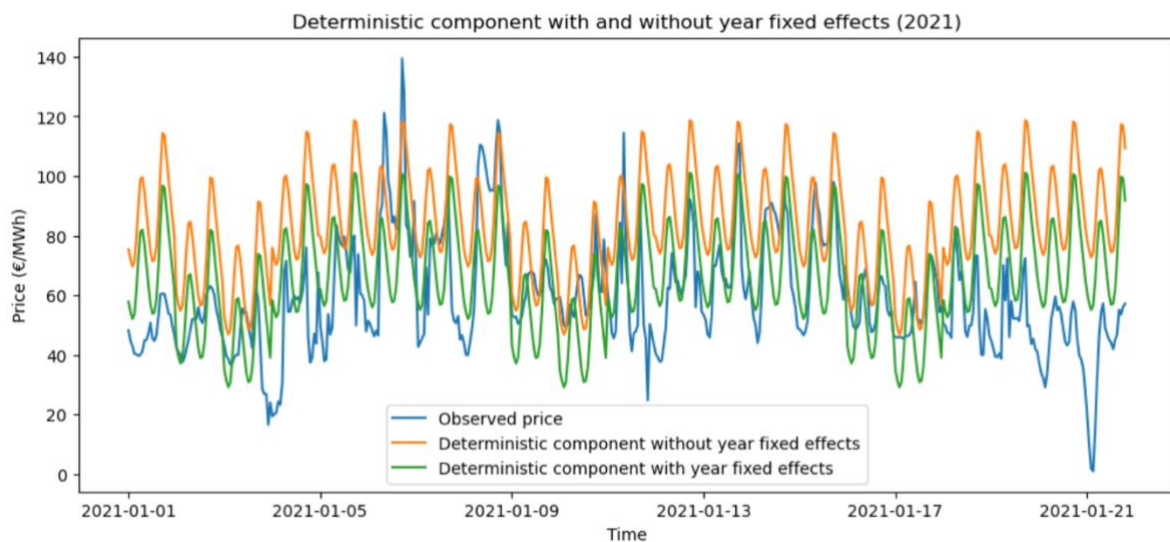


Figure 4.1. Observed prices and adjusted deterministic component for January 2021

¹⁰ Janczura et al. (2013) show that extreme observations can significantly influence the estimation of seasonal components in electricity prices and review several filtering or correction methods used to mitigate this issue. In the same spirit, this study aims to reduce the influence of extreme observations while preserving the full dataset. Rather than filtering observations, the deterministic component is adjusted through a constant re-centering of its mean level.

In the next figure, the deterministic component illustrates how electricity prices vary depending on the time of day over the full sample period (2016-2026). Negative prices observed around midday may be associated with periods of high renewable energy production, while higher prices typically occur during peak demand hours, particularly around 5-6 p.m.

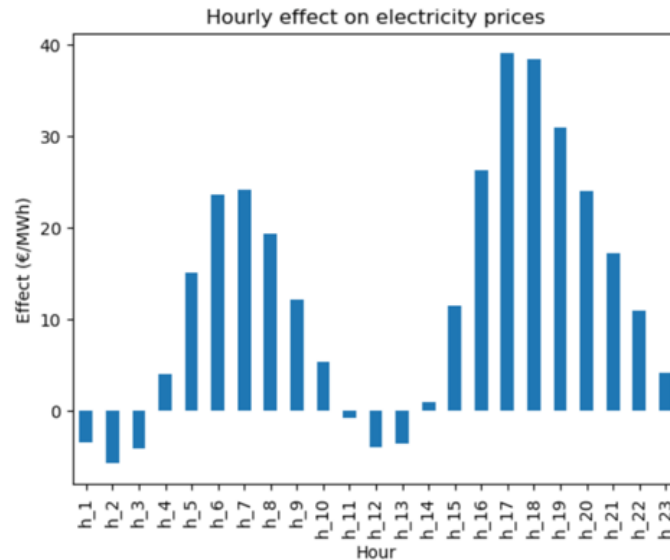


Figure 4.2. Average hourly deterministic effect on electricity prices

4.2.4.2 Analysis and decomposition of residuals

The residual component R_t , defined as the difference between observed prices and the deterministic component, captures the remaining stochastic variability in electricity prices not explained by calendar effects.

To account for this, residuals are decomposed into:

$$R_t = X_t + J_t \quad (4.7)$$

where:

- X_t represents the **normal component**, capturing regular price fluctuations around the mean.
- J_t represents the **spike component**, capturing extreme price movements.

This decomposition allows distinguishing between typical market behavior and rare but significant events.¹¹ Both components are described separately in the following sections.

The figure below shows the distribution of all residuals (normal and spike), highlighting that most price deviations are concentrated around zero. This indicates that observed prices are generally close to their expected (deterministic) level, while extreme values beyond the percentile thresholds correspond to spike events.

¹¹ This decomposition is conceptually inspired by the electricity price literature, which recognises that electricity prices combine regular fluctuations with occasional spike events and that standard mean-reverting dynamics alone may not fully capture extreme price movements (Huisman & Mahieu, 2003; Cartea & Figueroa, 2005). However, rather than estimating a regime-switching or jump-diffusion process, the present specification adopts a simplified empirical specification in which residuals are decomposed into a normal AR(1) component and a separately calibrated spike component identified through empirical thresholds and time-varying occurrence probabilities.

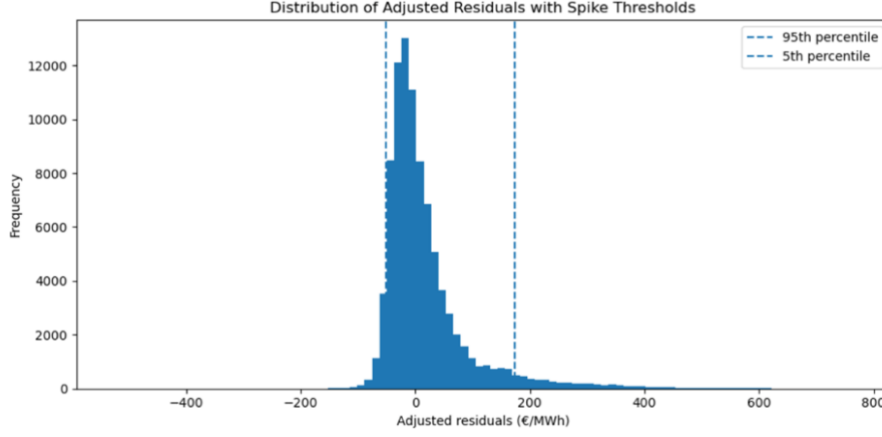


Figure 4.3. Distribution of adjusted residuals with spike thresholds

4.2.4.3 Modeling of the normal component (X_t) (AR(1))

Since X_t and J_t are not directly observable separately, observations classified as extreme events are filtered out using percentile-based thresholds in order to estimate the regular dynamics separately.

The remaining filtered residual series is then modeled as the normal component using an autoregressive process of order 1 (AR(1)):

$$X_t = \phi X_{t-1} + \varepsilon_t \quad (4.8)$$

where:

- X_t is the normal component at time t
- X_{t-1} is the value of the normal component at the previous time step,
- ϕ is the autoregressive coefficient,
- ε_t is a random innovation term (white noise), derived from the residuals of the AR(1) model and representing the unpredictable component of normal price fluctuations,

The autoregressive coefficient ϕ measures the strength of temporal persistence in the normal component of electricity prices, that is, the extent to which normal deviations from the deterministic price level depend on previous realizations of the normal residual component. In practical terms, persistence means that temporary deviations from the deterministic price component do not disappear immediately but tend to decay progressively over subsequent hours. The estimated autoregressive coefficient satisfies $0 < \phi < 1$, where a value of ϕ close to 1 indicates that shocks have long-lasting effects, while lower values imply faster mean reversion.¹²

The parameter was estimated empirically using ordinary least squares (OLS) applied to the normal component after excluding spike observations. Since the electricity price process is

¹² Janczura and Weron (2010) and Ziel (2016) highlight the strong autoregressive and mean-reverting behaviour of electricity prices. While these studies rely on more elaborate autoregressive specifications, such complexity falls beyond the scope of this thesis. Therefore, the present study adopts a simplified AR(1) representation to capture persistence in normal price fluctuations.

modeled at hourly frequency, persistence in the normal component is estimated between consecutive hours.

Table 4.2. Estimation results of the baseline AR(1) model

Parameter	Estimate	Std Error	t-stat	p-value
phi	0.9	0.001	621	<0.001
Observations	90071			
R_squared	0.811			
Durbin_Watson ¹³	2.178			

Source: author's calculations based on ENTSO-E data.

The estimated coefficient ($\hat{\phi} = 0.900$) is highly statistically significant and indicates strong hourly persistence in the normal component of electricity prices. A one-hour deviation therefore remains strongly reflected in the following hour, although its effect progressively decreases over time.

The relatively high explanatory power of the model ($R^2 = 0.811$) suggests that approximately 81% of the variation in the normal component is explained by its lagged value. In addition, the Durbin-Watson statistic remains close to 2, indicating limited remaining serial correlation after estimation and supporting the adequacy of the AR(1) specification.

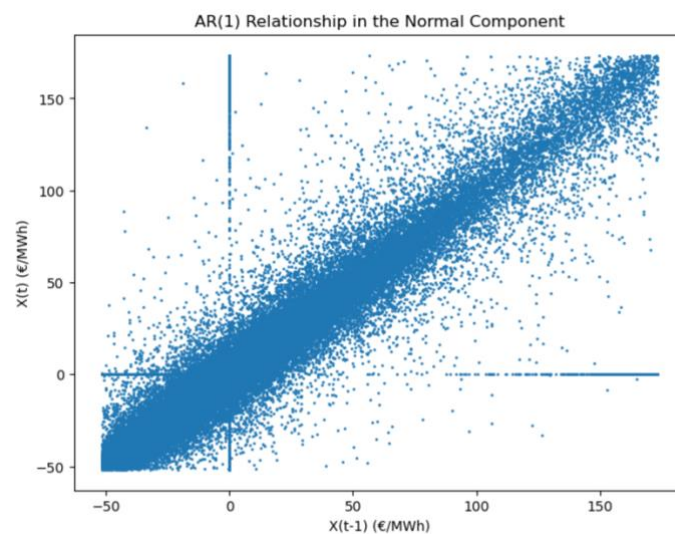


Figure 4.3. Relationship between X_t and X_{t-1} in the normal component

The strong linear relationship observed between X_t and X_{t-1} illustrates the persistence captured by the autoregressive coefficient and confirms that the current value of the normal component remains strongly dependent on its previous value.

To assess whether persistence may operate across days rather than across consecutive hours, an additional robustness check was performed using a 24-hour lag specification.

$$X_t = \phi X_{t-24} + \varepsilon_t$$

¹³ The Durbin-Watson statistic assesses whether residuals remain serially correlated after estimation. Values close to 2 suggest limited residual autocorrelation, values below 2 indicate positive autocorrelation, and values above 2 indicate negative autocorrelation (Wooldridge, 2020).

Table 4.3. Robustness check: Daily persistence (AR(24))

Parameter	Estimate	Std Error	t-stat	p-value
phi_24	0.763	0.002	354.2	0
Observations	90048			
R_squared	0.582			
Durbin_Watson	0.639			

Source: author's calculations based on ENTSO-E data.

The alternative specification confirms the existence of statistically significant persistence across equivalent hours of consecutive days. However, its explanatory power remains lower than the baseline hourly specification ($R^2 = 0.582$ versus 0.811).

This result suggests that normal residual electricity price dynamics are primarily driven by short-term hourly dependence rather than by inter-day persistence. Since deterministic daily patterns are already captured separately, the hourly AR(1) specification is retained for the Monte Carlo simulation framework.

4.2.4.4 Modeling of Spike Component (J_t)

Conceptual framework of Spike Modeling

The spike component (J_t) captures extreme price movements that are not explained by the deterministic seasonal component (μ_t) nor by the normal stochastic fluctuations (X_t). These spikes correspond to rare but significant market events, such as periods of system stress, unexpected demand surges, or supply shortages.

The spike component is estimated after isolating the deterministic component. Residual observations exceeding predefined thresholds are interpreted as empirical spike events and are used to calibrate spike occurrence and magnitude distributions. This decomposition is used for estimation purposes and provides an operational approximation allowing regular and extreme dynamics to be calibrated separately.

Historical identification of spike events

Spike observations correspond to residual values exceeding empirical thresholds defined from the residual distribution

$$J_t = \begin{cases} R_t & \text{if } R_t < q_5 \text{ or } R_t > q_{95} \\ 0 & \text{otherwise} \end{cases}$$

Observations not classified as spikes are assigned to the filtered normal component ($X_t = R_t - J_t$). This filtering procedure allows regular price dynamics and extreme events to be calibrated separately. In this study, observations are classified as spikes using the following thresholds: a positive spike threshold of +173.5 €/MWh and a negative spike threshold of −51.7 €/MWh.¹⁴

The figure below illustrates the residuals over 2016-2026 and highlights the occurrence of extreme price events (spikes), identified using empirical thresholds.

¹⁴ This approach is inspired by the electricity price spike literature, where spikes are often identified as extreme observations located in the tails of the price distribution. Stathakis et al. (2021), for example, identify extreme events using threshold-based methods within an EVT/POT framework. In contrast, the present study does not estimate an EVT model but adopts a simplified empirical classification based on the 95th and 5th percentiles of the residual distribution.

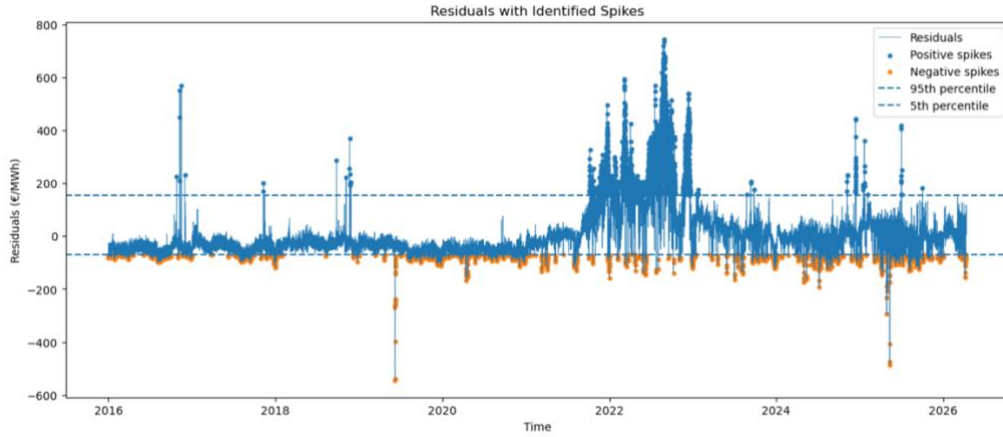


Figure 4.4. Residuals and identified spike events (2016-2026)

Modeling Spike Occurrence probabilities

Once historical spikes are identified, their occurrence probability is modeled using time-varying probabilities, which are estimated empirically from the data by computing the frequency of spikes conditional on calendar variables such as the hour of the day and the month. This captures the fact that extreme events may be more likely during specific periods, such as peak demand hours. Spike occurrence therefore depends on time-related factors.¹⁵

Spike occurrence is assumed to vary over time and is modeled using calendar-dependent probabilities conditional on hour of day and month.

For each hour–month cell:

$$p_{\{h,m\}} = P(\text{spike} \mid h, m)$$

estimated as:

$$p_{\{h,m\}} = \frac{\text{number of spike observations}}{\text{number of observations}}$$

Robust calibration and smoothing procedure

However, it should be noted that some hour-month cells can be strongly influenced by some years. In particular, the year 2022, characterized by exceptional price volatility, may disproportionately affect the estimated spike frequencies in certain periods. To assess the sensitivity of the calibration to this exceptional market regime, spike frequencies are compared using specifications estimated with and without 2022.

¹⁵ The electricity price literature shows that spike occurrences vary over time and depend on factors such as the hour of the day, the day of the week, and demand conditions. Kostrzewski and Kostrzewska (2021), for instance, model spike probabilities using a generalized ordered logit framework. The present study adopts a simplified non-parametric empirical approach based on observed spike frequencies conditional on calendar effects.

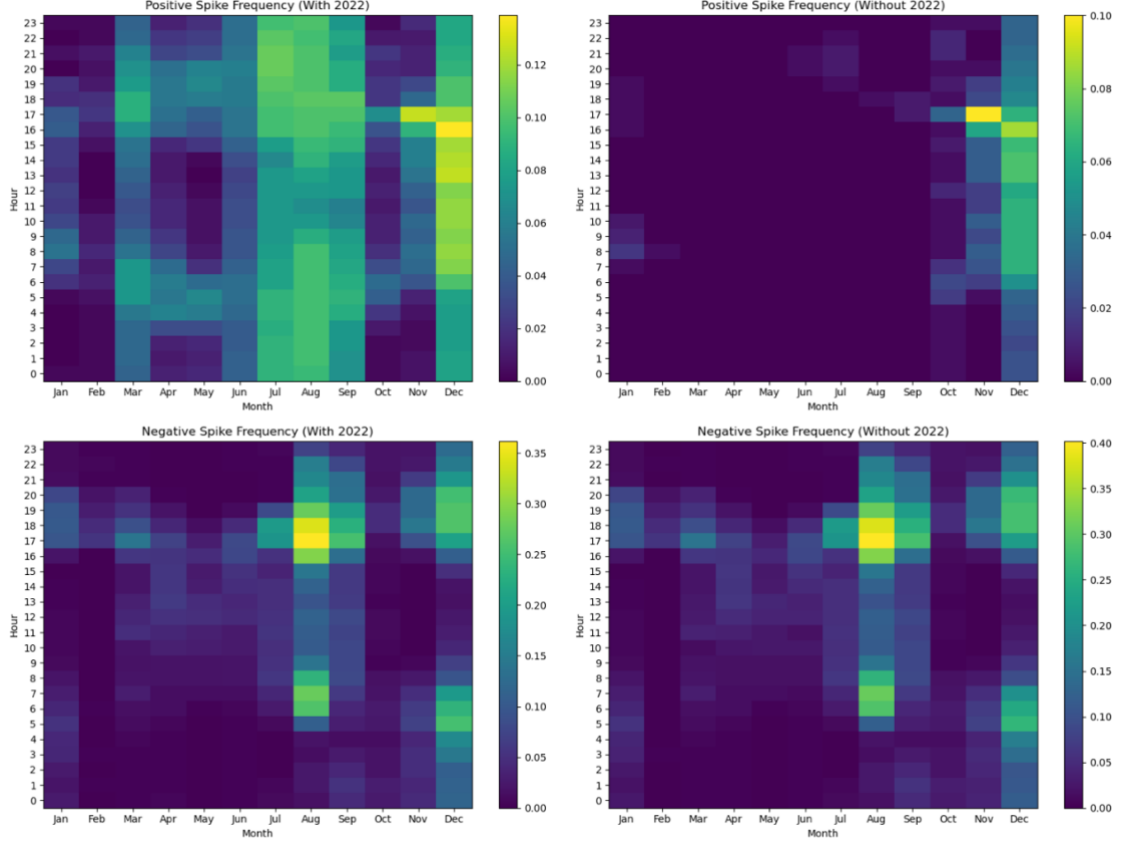


Figure 4.5. Comparison of positive and negative spike frequencies estimated with and without 2022

Figure 4.5 shows that including 2022 increases estimated spike frequencies during specific months and hours, particularly for positive spikes. Nevertheless, positive spike events remain concentrated in specific periods, especially during the end of the year, even when 2022 is excluded, suggesting that these temporal patterns are not solely driven by the exceptional market conditions observed in 2022.

Rather than removing this period from the calibration dataset, the present study retains 2022 because it reflects a real market regime that future simulations may plausibly encounter. However, to reduce the influence of isolated historical events and improve robustness, an additional smoothing procedure is introduced.

An hour–month cell is considered robust only if at least one spike is observed in that cell in at least two distinct years. This criterion aims to ensure that elevated spike probabilities are not driven by a single exceptional episode. Since the calibrated spike process serves as the baseline specification for subsequent scenario simulations, the objective is to preserve the broad historical structure of spike occurrence while avoiding excessive dependence on isolated historical realizations.

So, if the robustness condition is satisfied, the empirical probability is retained:

$$p_{h,m} = p_{\{h,m\}}^{raw}$$

Otherwise, the probability is partially pooled toward the global spike frequency:

$$p_{\{h,m\}}^{smooth} = \alpha p_{global} + (1 - \alpha) p_{\{h,m\}}^{raw}$$

where p_{global} is the average spike probability over the full sample¹⁶ and $p_{\{h,m\}}^{raw}$ is the raw probability estimated for the corresponding hour-month cell.

This approach avoids overfitting to isolated historical events while still preserving some information from the local pattern.¹⁷

The smoothing parameter is set to $\alpha = 0.7$, giving greater weight to the global probability than to the local estimate. This choice reflects the limited robustness of many local spike patterns, while still preserving part of the observed seasonal structure. It can thus be seen as a pragmatic balance between stability and fidelity to historical data.

With this level of smoothing, hour-month cells with no observed spikes are assigned a small but non-zero probability of occurrence. This may appear to introduce spikes in periods where none were historically observed, but it prevents the model from assigning zero probability to rare but plausible events and reduces sensitivity to isolated observations.

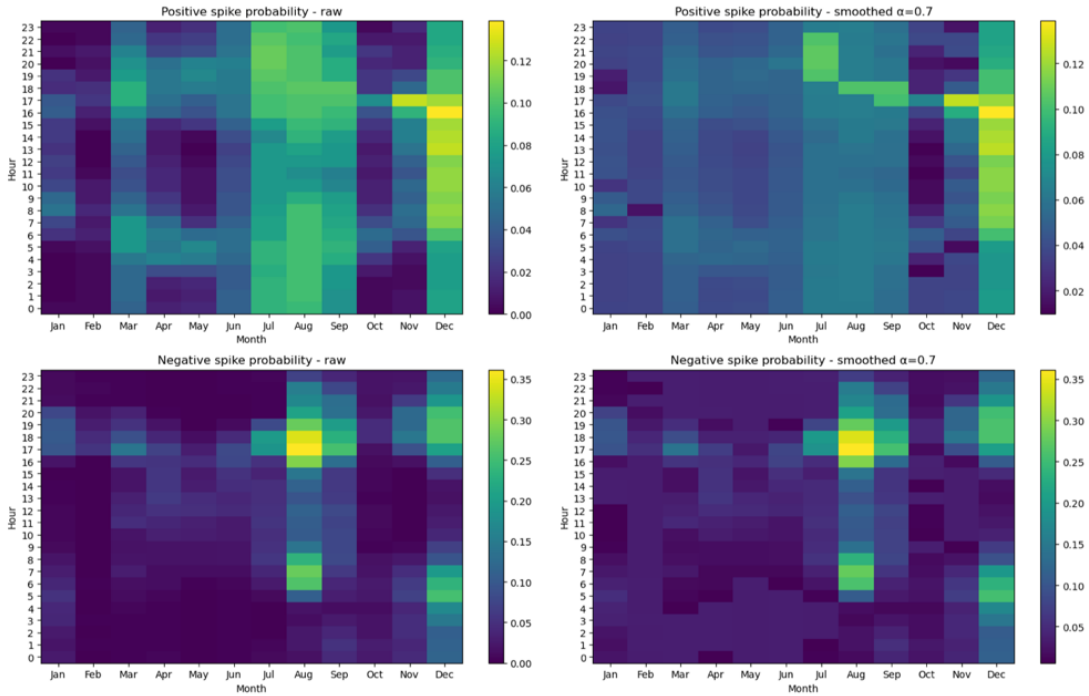


Figure 4.6. Raw and smoothed spike probabilities across hour-month cells

Figure 4.6 illustrates the effect of the smoothing procedure on the estimated spike probabilities. The smoothed specification preserves the main seasonal and intraday spike patterns observed in the raw probabilities, while reducing isolated local variations and preventing extreme probabilities driven by a limited number of observations. Alternative smoothing specifications were evaluated as a sensitivity analysis (see Appendix D).

Modeling of Spike Magnitude

¹⁶ The global spike probability p_{global} is approximately 5.0% (0.0500044) for both positive and negative spikes.

¹⁷ Zhao et al. (2010) discuss shrinkage approaches as a way to stabilize noisy local estimates by partially pooling them toward a more stable aggregate estimate. Inspired by this general logic, the present study smooths non-robust spike probabilities toward the global spike frequency.

Once the occurrence of a spike has been simulated, the model assigns a magnitude to the spike component J_t . In other words, the occurrence model determines whether a spike takes place, while the magnitude model determines how large this spike is.

Conditional on spike occurrence, magnitudes are drawn from empirical distributions estimated from historical spike residuals.¹⁸ Positive and negative spikes are modeled separately, since they exhibit different statistical properties and different tail behaviors. In particular, negative spikes appear substantially less sensitive to yearly composition effects than positive spikes (Figure E1 in Appendix E). This relative stability may reflect the existence of a lower bound on electricity prices, as they cannot become very negative, which mechanically constrains the dispersion of negative spikes and limits the influence of individual years on the estimated spike magnitude profile.

Since spike occurrence and spike magnitude are modeled separately, the weighting scheme for spike magnitudes is not intended to reflect the frequency of spike events across years, but rather the distribution of spike sizes conditional on spike occurrence. Each year therefore initially receives equal weight when generating spike magnitudes, independently of the number of observed spikes observed in that year.

Construction of yearly empirical distributions

Spike magnitudes are generated in two stages. First, a year is randomly selected according to predefined weights and second, a spike magnitude is drawn from the empirical distribution corresponding to that year. All full years are initially assigned equal weights, while the partial year 2026 is assigned a lower weight proportional to its data coverage.

Exploratory analysis of yearly spike magnitudes

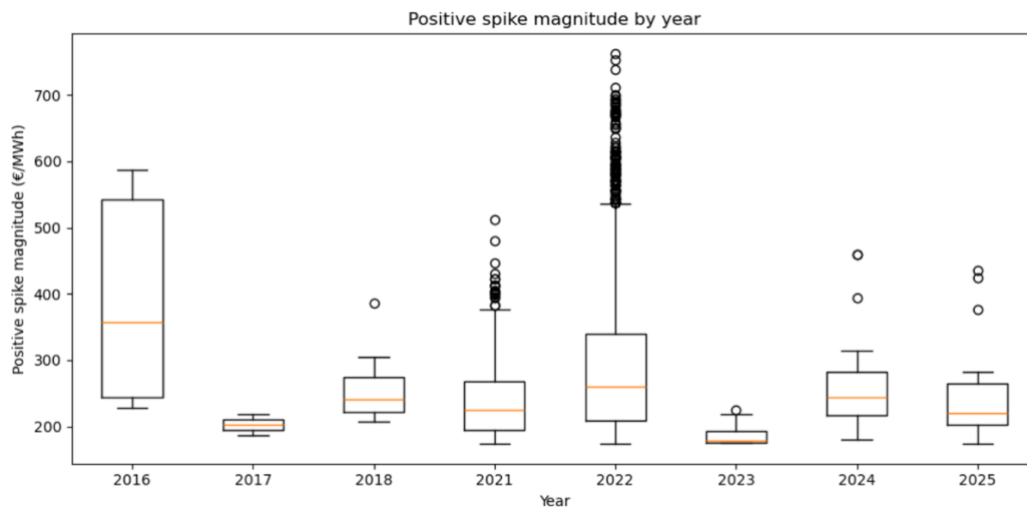


Figure 4.7. Distribution of positive spike magnitudes by year

Figure 4.7 illustrates the distribution of positive spike magnitudes across years. Since the objective is to model spike magnitude rather than spike frequency, years are compared based on the size and dispersion of observed spikes. The figure highlights heterogeneity between years. 2016 is characterized by a limited number of observations combined with relatively large

¹⁸ This specification is consistent with electricity price models that represent extreme price events through a separate spike component, where the occurrence of a spike and its magnitude are modeled distinctly, with spike magnitudes specified conditional on spike occurrence (Huisman and Mahieu, 2003; Cartea and Figueroa, 2005).

spike magnitudes, while 2022 exhibits both a high dispersion and numerous extreme values. Year 2021 also presents elevated dispersion compared to most years, whereas 2023 shows a more concentrated distribution. Years 2019 and 2020 are not displayed as they do not contain positive spike observations.

These observations are not used directly to determine the final weighting scheme but rather serve to motivate the robustness analysis presented below.

Robustness analysis of yearly weighting choices

Several alternative weighting schemes are evaluated in order to assess the sensitivity of simulated spike magnitudes to the treatment of atypical years.

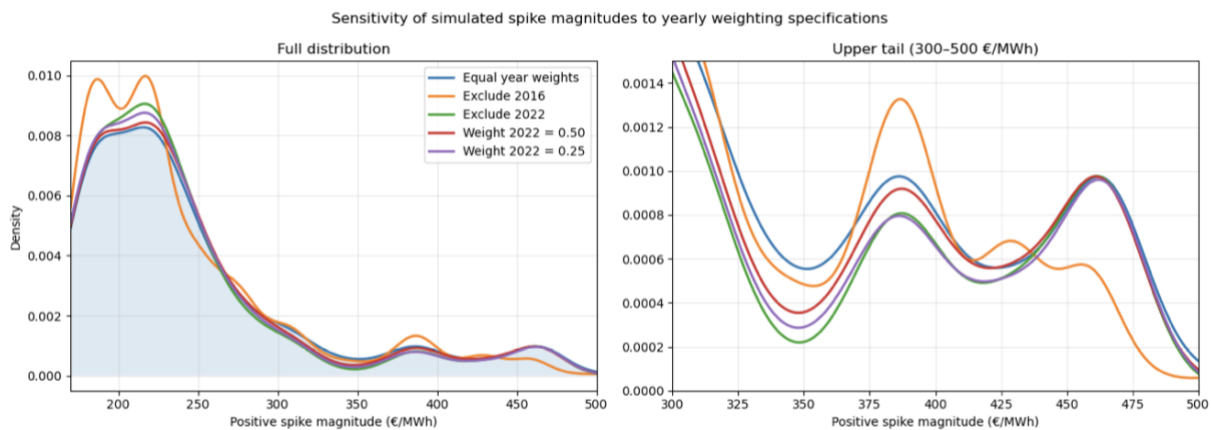


Figure 4.8. Sensitivity of simulated spike magnitudes to alternative yearly weighting specifications

Figure 4.8 compares the baseline specification, where all years receive equal weights, with alternative weighting schemes excluding selected years or reducing their contribution to the calibration. The left panel displays the full distribution of simulated positive spike magnitudes, while the right panel focuses on the upper tail (300-500 €/MWh) in order to highlight differences in extreme spike behavior.

Excluding 2016 noticeably modifies the profile of positive spike magnitudes. In particular, the exclusion of 2016 shifts the distribution toward higher spike magnitudes, especially in the 200-300 €/MWh range, while reducing the relative importance of the most extreme spikes (approximately 400-500 €/MWh). This suggests that the inclusion of 2016 has an influence on the spike magnitudes and affects the balance low intermediate and very high price spikes.

Adjustments applied to 2022 also affect the spike profile, although their influence appears more limited across most of the support. However, visible differences remain in the upper tail (300-500 €/MWh), indicating that the treatment of 2022 still affects the calibration of extreme price events.

Nevertheless, the spike magnitude curves alone do not allow conclusions regarding the actual impact on the result of the analysis. Therefore, a second robustness exercise is performed by directly evaluating how alternative weighting specifications affect estimated future reliability option repayments. This additional step allows to assess whether the observed differences in estimated spike magnitude translate into meaningful differences in simulation outcomes and whether modifications to the weighting scheme are justified.

Final specification

Figure 4.9 compares expected reliability option repayments under alternative yearly weighting specifications. The benchmark specification assigns equal weights to all years in the historical sample. Alternative specifications are obtained by modifying this benchmark only for the selected year, while keeping equal weights across all remaining years.

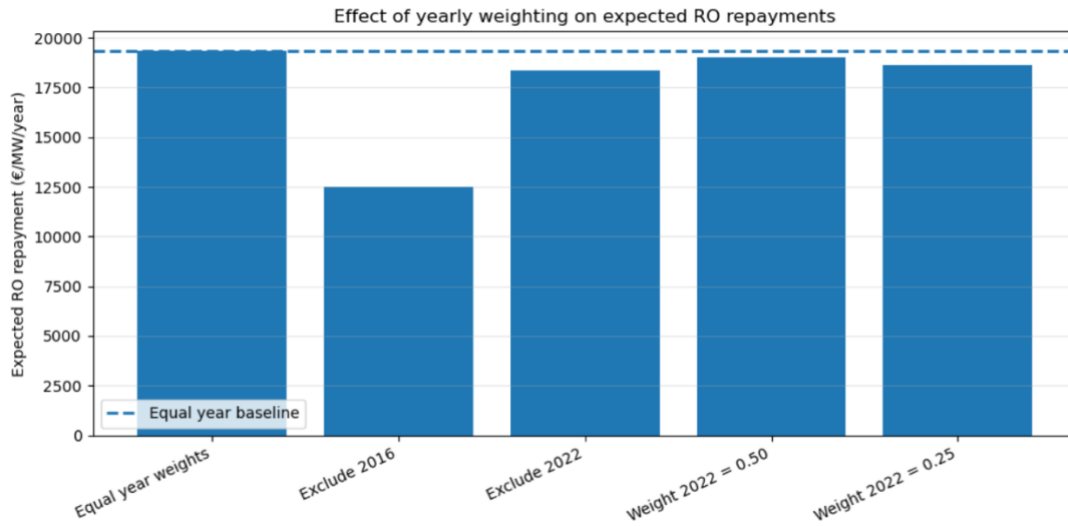


Figure 4.9. Sensitivity of expected reliability option repayments to alternative yearly weighting specifications

This robustness analysis suggests that the treatment of 2022 affects estimated reliability option repayments, but the magnitude of this effect remains relatively limited. Excluding 2022 entirely reduces expected repayments by approximately 5%, while partial down-weighting produces even smaller changes (between 2% and 4%).

By contrast, excluding 2016 leads to a substantially larger reduction in expected reliability option repayments (-35%), indicating that model outcomes are highly sensitive to the inclusion of this year. This result suggests that observations from 2016 have a strong influence on the resulting spike magnitude profile and on the frequency of simulated price episodes above the strike price.

Given the objective of constructing a relatively neutral baseline specification onto which alternative market scenarios are subsequently imposed, retaining a specification strongly driven by a single historical year may not be desirable. Therefore, the specification excluding 2016 while maintaining equal weights across the remaining years is retained as the baseline.

This choice preserves the overall historical market structure while limiting the influence of individual years on the baseline simulations.

4.2.4.5 Validation of the Price Process Specification

To assess whether each component of the electricity price process contributes meaningfully to reproducing realistic electricity market dynamics, a specification robustness test is conducted. Starting from a deterministic specification and progressively introducing stochastic persistence and spike dynamics, simulated price distributions are compared with historical observations using descriptive statistics and reliability-option-related indicators. See Appendix F.

4.2.4.6 Parameter calibration and reference configuration

The previous sections presented the structure of the electricity price model as well as the different parameters used to represent its components. To implement the simulation framework, these parameters were calibrated using historical electricity price data over the period 2016-2026.

This calibration defines a reference parameter configuration representing the expected evolution of electricity prices under the assumption that the dynamics observed historically continue into the future, in the absence of additional scenario-specific assumptions.¹⁹ This reference configuration constitutes the baseline scenario (reference scenario). Alternative scenarios are subsequently constructed through targeted adjustments of selected model parameters (μ_t , σ , spikes) in accordance with the assumptions underlying each scenario.

4.3 Alternative scenario construction & variation of the parameters

4.3.1 General logic behind the choice of scenarios

The Belgian electricity system is evolving in a context characterised by significant uncertainty, notably related to the pace of electrification, the development of renewable energy sources, the growth of flexibility and storage, as well as potential delays in infrastructure development and dependence on imports.

Within this context, Elia has defined three main trajectories for the 2026-2036 horizon²⁰: *Current Commitments & Ambitions*, *Constrained Transition*, and *Prosumer Power*. These scenarios are based on the main determinants of electricity prices, namely demand, the level of renewable generation, and the availability of flexibility.

However, due to the highly interconnected nature of the Belgian system, its adequacy also depends on conditions observed in neighboring countries, particularly regarding the availability of generation capacities and cross-border exchanges. In order to account for these external risks, a fourth scenario, referred to as a « regional stress » or « adequacy stress » scenario, is introduced. This scenario does not correspond to one of Elia's main scenarios, but is instead based on the EU-SAFE sensitivities, which describe more adverse conditions at the European level.

4.3.2 Scenario descriptions and expected market effects

4.3.2.1 Scenario 1: *Current Commitments & Ambitions*

Description

This scenario assumes that the energy and climate policies announced in Belgium and Europe are effectively implemented. It therefore includes progressive electrification in line with existing objectives, the development of renewable energy sources consistent with current plans, including both the continuation and expansion of photovoltaics and offshore wind, as well as a gradual increase in flexibility, notably supported by the growth of batteries and mechanisms such as the CRM. The scenario also incorporates already-decided elements, such as the extension of the Doel 4 and Tihange 3 reactors until 2035. This scenario therefore follows the projections of the Belgian Federal Planning Bureau, the NECP plans, recent governmental agreements, and industrial electrification plans.

¹⁹ However, certain methodological adjustments were introduced in order to limit the disproportionate influence of atypical years while preserving an overall dynamic representative of the historical sample.

²⁰ The scenarios are derived from the *Adequacy and Flexibility Study for Belgium 2026–2036* (Elia, 2025b), which presents different assumptions regarding the evolution of the Belgian energy mix by 2036.

This scenario therefore assumes neither a major blockage of the transition nor an extreme acceleration driven by consumers. It represents a “reasonable” trajectory: objectives continue to be pursued, but the transformation remains gradual.

Expected effect on prices

The average price is not radically different from the general scenario. However, the intra-day structure becomes more pronounced: lower prices during the day when solar production is high, but still higher prices in the evening and during winter periods. Although flexibility increases under this scenario, it remains insufficient to fully compensate for the variability of renewable generation.

4.3.2.2 Scenario 2: *Constrained Transition*

Description

The *Constrained Transition* scenario corresponds to a trajectory characterised by a slowdown in the energy transition, marked by constraints on supply chains, delays in certain policies, and more limited acceptance of infrastructure projects (networks and wind power). In Belgium, delays in offshore projects and interconnections have notably already been observed.

This scenario also translates into slower electrification, delayed adoption of electric vehicles and heat pumps, as well as more limited development of flexibility. This leads to downward revisions in electricity consumption assumptions and delays in renewable projects.

Among the different scenarios considered, this trajectory is the most consistent with the reference scenario retained in the CRM calibration exercises for the 2027-28, 2028-29, and 2030-31 periods, which rely on more constrained transition assumptions. These notably include Belgian electricity demand levels of 88.4 TWh, 90.8 TWh, and 95.8 TWh respectively, as well as reductions in flexibility volumes (DSR), delays in certain offshore projects (particularly PEZ I), a progressive but limited deployment of batteries, and sensitivity to reduced availability of the French nuclear fleet during winter periods (Elia, *Calibration Report*, December 2025).

Expected effect on prices

This scenario does not automatically imply significantly higher average prices, because demand is lower. However, it mainly implies a less efficient transition: fewer renewables than expected, less flexibility, fewer batteries, and therefore less downward pressure on daytime prices and greater dependence on thermal generation during certain hours.

4.3.2.3 Scenario 3: *Prosumer Power*

Description

The *Prosumer Power* scenario corresponds to an acceleration of the transition on the consumer side. Declining costs of photovoltaics, residential batteries, and electric vehicles make these technologies more accessible, thereby encouraging their adoption. This scenario also assumes faster deployment of heat pumps, as well as greater development of residential flexibility and decentralised equipment.

It is therefore not merely a “greener” scenario, but rather a system in which consumers play a more active role: they produce, store, and adapt their consumption, thereby modifying the demand profile. This evolution is consistent with certain recent trends observed in Belgium, where high levels of renewable generation have already been reached during certain periods (more than 10 days with a combined hourly wind and PV share exceeding 90% of demand have been recorded).

Expected effect on prices

This scenario mainly modifies the structure of prices. It is characterised by increased price polarisation, with low or even negative prices during daytime periods of strong solar production. By contrast, prices remain somewhat higher in the evening, when renewable generation decreases while demand remains relatively strong, despite a partial mitigation effect resulting from the development of flexibility.

4.3.2.4 Scenario 4: Regional stress / Adequacy stress

Description

This scenario differs from the previous three insofar as it does not correspond to a structural trajectory, but rather to a stress situation resulting from the combination of several constraints. It follows the logic of the EU-SAFE sensitivities developed by Elia, which aim to evaluate the impact of adverse conditions at the European level.

Unlike Elia's approach, which generally analyses these risks separately, this scenario proposes combining the factors considered most relevant for the Belgian system by 2030. These notably include reduced availability of the French nuclear fleet, lower renewable generation due to adverse weather conditions, constraints on cross-border exchanges (interconnections / minRAM), as well as delays in the development of certain Belgian offshore capacities (Princess Elisabeth Zone / Modular Offshore Grid II).

The highly interconnected nature of the Belgian electricity system makes this scenario particularly relevant. Prices and adequacy do not depend solely on the national generation mix, but also on conditions in neighbouring countries, especially those with which Belgium is directly interconnected, such as France, the Netherlands, Germany, and the United Kingdom.

Expected effect on prices

The constraints do not apply continuously; they mainly affect critical periods, particularly during winter and peak hours. This results in an increase in both the frequency and intensity of high-price episodes. Average prices increase, but the main effect remains the thickening of the right tail of the price distribution.

4.3.3 Scenario translation into model variables

Since Elia scenarios are not expressed directly in terms of model parameters, the qualitative mechanisms identified in each scenario are translated into modifications of selected components of the electricity price model.

The objective here is not to estimate parameter values but to determine which dimensions of the price process are expected to evolve under each scenario.

Table 4.4. Translation of Elia scenarios into electricity price model variables

Scenario	Main mechanisms identified	Expected impact on electricity price formation	Model variables adjusted
Current Commitments (CC)	Progressive RES deployment; moderate electrification; increasing flexibility; no major structural break	More frequent low-price periods due to higher renewable generation; limited evening scarcity; overall price level remains close to historical dynamics	$\Delta\mu \downarrow$; $\sigma \uparrow$ (slightly) ; Negative spike probability $\uparrow$; Negative spike magnitude $\uparrow$ (slightly)
Constrained Transition (CT)	Slower electrification and lower demand growth; lower RES deployment; lower flexibility availability; stronger dependence on thermal generation and CO ₂ costs	Slower electrification slightly reduces demand pressure, but lower renewable deployment and reduced flexibility dominate, resulting in more frequent scarcity episodes and higher average prices.	$\Delta\mu \uparrow$; $\sigma \uparrow$; Positive spike probability $\uparrow$; Positive spike magnitude $\uparrow$; Negative spikes $\downarrow$

Prosumer Power (PP)	Strong decentralised PV deployment; higher self-generation; daytime oversupply; stronger evening ramp effects	More frequent low-price periods during solar hours combined with sharper evening price recoveries, resulting in greater intra-day price contrasts	$\Delta\mu \downarrow$; $\sigma \uparrow$; Negative spike probability $\uparrow\uparrow$; Negative spike magnitude $\uparrow$; Positive spikes $\uparrow$ (moderately)
Regional Stress / Adequacy Stress	Regional supply constraints; lower import availability; tighter adequacy margins; stronger thermal and scarcity-based price-setting	More frequent and stronger scarcity price episodes, leading to a higher occurrence of extreme prices and an upward shift of the right tail of the distribution	$\Delta\mu \uparrow\uparrow$; $\sigma \uparrow\uparrow$; Positive spike probability $\uparrow\uparrow$; Positive spike magnitude $\uparrow\uparrow$; Negative spikes $\downarrow$

The final parameter values retained for each scenario are reported below.

4.3.4 Explicit effect on model variables

Numerical values are not estimated econometrically. Instead, parameter values are calibrated iteratively by combining (i) the qualitative mechanisms described in Elia's scenarios and (ii) the quantitative information publicly reported in the Adequacy & Flexibility Study for Belgium.

Because Elia's scenario documentation does not provide parameter values directly transferable to the price model, scenario assumptions are translated into modifications of selected model variables. The resulting price process is then simulated and compared with the scenario outcomes reported by Elia. In particular, simulated average electricity prices are used as an external plausibility benchmark, as Adequacy & Flexibility report provides indicative average price ranges across scenarios over the 2027–2037 horizon.

The calibration therefore follows an iterative procedure: scenario assumptions are translated into parameter adjustments, electricity prices are simulated, resulting outputs are compared with Elia's scenario outcomes, and parameters are refined when necessary, until the simulated distributions remain broadly consistent with the expected scenario behaviour. Additional scenario-specific assumptions reported by Elia are incorporated where available. Detailed calibration choices and supporting calculations are provided in Appendix H.

Table 4.5 summarizes the main scenario-specific parameter adjustments introduced in the price model in order to reflect the expected market dynamics associated with each scenario.

Table 4.5. Scenario-specific adjustments applied to electricity price model variables

Scénario	Delta μ_t	Volatility (σ)	Positive spikes	Negative spikes	Average price
Current Commitments	-0.98 €/MWh on average; -4.5 solar ; +2 evening	$\times 1.10$	probability $\times 1.05$; magnitude $\times 1.00$	probability $\times 1.20$; magnitude $\times 1.05$	70.9 €/MWh
Constrained Transition	+1.09 €/MWh on average; -2 solar ; +10 winter/evening	$\times 1.15$	probability $\times 1.30$; magnitude $\times 1.10$	probability $\times 0.80$; magnitude $\times 0.95$	79.7 €/MWh
Prosumer Power	-3.79 €/MWh on average; strong solar decline (-5 à -16) ; +2 à +5 evening	$\times 1.35$	probability $\times 1.15$; magnitude $\times 1.05$	probability $\times 1.70$; magnitude $\times 1.15$	67.4 €/MWh
Stress régional	+9.51 €/MWh on average ; strong winter/evening increase (+17 à +34) ; overall increase	$\times 1.45$	probability $\times 2.00$; magnitude $\times 1.25$	probability $\times 0.80$; magnitude $\times 1.00$	101.6 €/MWh

**These values do not represent exact forecasts.*

4.3.5 Calibration validation

Table 4.6 summarizes the main validation checks used to assess whether the simulated electricity price dynamics remain broadly consistent with the indicative outcomes reported in Elia's scenarios.

Table 4.6. Validation checks comparing simulated outcomes with Elia scenario benchmarks

Validation indicator	Elia reference	Simulated result	Assessment
Baseline / Current Commitments average price	Average prices over the 2027–2037 horizon remain broadly within 60–80 €/MWh ²¹	Historical baseline: 72.14 €/MWh ; CC: 70.9 €/MWh	Within expected range
CT premium relative to CC	CT average prices remain approximately 5–10 €/MWh higher than CC / PP ²²	CT – CC = +8.8 €/MWh (79.7 – 70.9)	Consistent
PP relative to CC	Average price levels remain broadly comparable between PP and CC ²³	PP – CC = –3.5 €/MWh (67.4 – 70.9)	Consistent with slightly stronger downward pressure
Regional Stress premium relative to CC	Gas and stress assumptions may generate an increase of approximately 25–35 €/MWh ²⁴	Stress – CC = +30.7 €/MWh (101.6 – 70.9)	Consistent
Low-price occurrence (qualitative check)	More low-price periods expected under high RES scenarios	Higher negative spike frequency in CC and PP simulations	Consistent

Source: author's calculations based on Elia Adequacy & Flexibility Study assumptions.

Validation does not demonstrate parameter correctness but indicates that the combined effect of parameter adjustments produces outcomes broadly consistent with Elia scenario expectations.

4.4 Monte Carlo Simulation

4.4.1 Monte Carlo Simulation Framework

Monte Carlo simulations are used to repeatedly generate future electricity price trajectories based on the calibrated price process and the scenario configurations introduced in the previous section. The simulation procedure itself remains unchanged across scenarios, only the parameter values vary according to the underlying scenario assumptions.

The following sections describe how a single simulated trajectory is generated before repeating this procedure across a large number of simulations.

For each simulation s and each time step t , the simulated price is constructed as:

$$P_t^s = D_t + X_t^s + J_t^s$$

²¹ Figure 10-53 in Elia's Adequacy & Flexibility report.

²² Figure 10-53 in Elia's Adequacy & Flexibility report.

²³ Figure 10-53 in Elia's Adequacy & Flexibility report.

²⁴ Figure 10-54 in Elia's Adequacy & Flexibility report.

where D_t , X_t^s , and J_t^s denote respectively the deterministic, normal, and spike components, whose specification and calibration were introduced in the modeling section²⁵.

4.4.1.1 Simulation of the deterministic component

For the simulation horizon, a future calendar is constructed at an hourly frequency, and the deterministic component is computed directly from the estimated regression coefficients. As a result, it does not involve any randomness and remains identical across simulations, while varying over time according to the future calendar, thereby capturing hourly, weekly, and seasonal patterns.

4.4.1.2 Simulation of the Normal component

The normal component is simulated recursively using the estimated AR(1) process.

Prior to simulation, the empirical innovations are re-centered to ensure a zero-mean shock process. This adjustment prevents artificial drift in simulated prices and ensures that the normal component fluctuates around the deterministic price level.

The simulated trajectories are then generated according to:

$$X_t^s = \phi X_{t-1}^s + \varepsilon_t^s$$

where ε_t^s is independently drawn at each time step from the re-centered empirical distribution of the innovation terms obtained from the AR(1) estimation of the normal component.

For each trajectory, the process is initialized with a starting value X_0^s , equal to the last observed value of the normal component in the historical dataset. This choice ensures that the simulation starts from a realistic market state, preserving continuity between historical observations and simulated trajectories²⁶.

4.4.1.3 Simulation of the Spike component

During historical calibration, residual observations classified as spikes are temporarily separated from regular fluctuations in order to estimate normal and spike dynamics independently. This filtering procedure is introduced for parameter estimation only and should not be interpreted as implying that spike magnitudes are directly observed independently from normal fluctuations in historical data.

During simulation, both components are recombined to reconstruct complete future price trajectories, where regular stochastic variability and occasional spike events may occur simultaneously. This reflects the assumption that extreme price events occur on top of regular market fluctuations rather than replacing them entirely.

²⁵ This simulation approach is consistent with the reliability option literature. Andreis et al. (2020) value reliability options by modelling future electricity price trajectories under stochastic electricity price processes and estimating option values through Monte Carlo simulations. In their empirical application, 10,000 simulated electricity price paths are generated and the reliability option payoff is computed for each trajectory. While the electricity price model adopted by Andreis et al. (2020) differs from the one developed in this thesis, both approaches follow the same simulation logic of generating future electricity price trajectories and evaluating the resulting reliability option outcomes.

²⁶ Hyndman and Athanasopoulos (2021) describe forecasting procedures in which future values are generated recursively from the current estimated state of the process. Consistent with this logic, the present study initializes simulated trajectories using the last observed value of the normal component.

Enforcing $X_t = 0$ during spike periods would suppress the autoregressive dynamics estimated for the normal component and imply that short-term persistence disappears whenever a spike occurs. This would constitute a stronger structural assumption than the empirical filtering procedure adopted for calibration. The selected approach therefore preserves the autoregressive behavior captured by the normal component while allowing additional extreme deviations through the spike component.

The spike calibration procedure described in Section 4.2.4.4 provides the occurrence probabilities and empirical magnitude distributions used to generate future spike events within the Monte Carlo framework.

At each simulation step, spike occurrence is generated using Bernoulli draws:

$$O_{\{t,+\}}^s \sim \text{Bernoulli}(p_{t,+}), \quad O_{\{t,-\}}^s \sim \text{Bernoulli}(p_{t,-})$$

where:

$$\begin{cases} p_t = p_{\{h,m\}}^{\text{raw}} & , \text{if robust cell} \\ p_t = p_{\{h,m\}}^{\text{smooth}} & , \text{otherwise} \end{cases}$$

Conditional on occurrence, spike magnitudes are sampled from the calibrated empirical distributions $(M_{\{t,+\}}^s, M_{\{t,-\}}^s)$.

The spike component is then constructed as:

$$J_t^s = I_{\{t,+\}}^s M_{\{t,+\}}^s + I_{\{t,-\}}^s M_{\{t,-\}}^s \quad (4.9)$$

Depending on the scenario considered, selected spike parameters (occurrence probabilities and/or spike magnitudes) are adjusted relative to the reference calibration according to the scenario assumptions introduced previously.

4.4.1.4 Simulation procedure

The simulation proceeds recursively over time for each trajectory:

- A future hourly calendar is constructed over a one-year simulation horizon (8760 hours).
- The deterministic component D_t is computed for each time step.
- The normal component X_t^s is simulated recursively using the AR(1) process.
- The spike component J_t^s is generated at each time step based on the estimated occurrence probabilities and empirical magnitude distributions.
- The three simulated components are then combined to obtain the simulated electricity price trajectory P_t^s .

This procedure is repeated for a large number of simulations (1000 trajectories), resulting in a matrix of simulated prices with dimensions (t, s) , where t is the number of time steps and s the number of simulations. To assess the numerical stability of the Monte Carlo estimates, additional convergence tests were performed using 200, 500, 2,000 and 5,000 trajectories under different scenarios. Since the expected reliability option repayments remained highly stable beyond 1,000 simulations, 1,000 trajectories were retained for the analysis (see Appendix G).

To illustrate the simulation mechanism, graphical examples are presented for the reference parameter configuration (baseline scenario).

The simulated trajectories shown below are generated over a synthetic one-year horizon and represent a range of plausible future electricity price trajectories consistent with the statistical properties observed in the historical data.

Figure 4.10 illustrates a subset of simulated electricity price trajectories generated under the baseline calibration. The graph highlights the high variability of simulated electricity prices, including occasional extreme spikes, while preserving the seasonal patterns captured by the deterministic component.

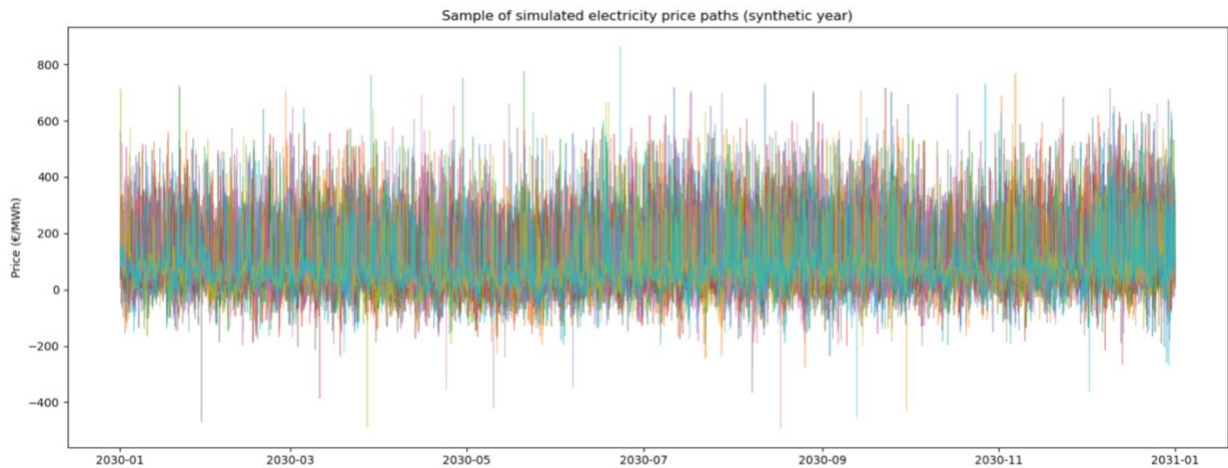


Figure 4.10. Sample of simulated electricity price trajectories under the baseline calibration

While the previous figure illustrates individual simulated trajectories, the following figure summarizes the overall distribution of simulated prices under the baseline scenario. The median trajectory reflects the expected seasonal pattern, while the shaded area (10th-90th percentile range) illustrates the uncertainty around future prices.

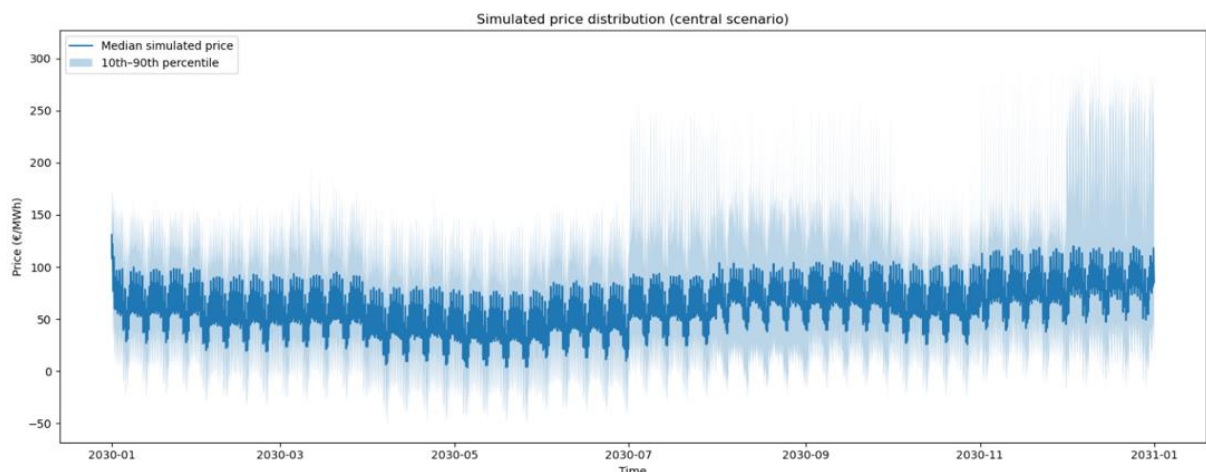


Figure 4.11. Median simulated electricity price and 10th–90th percentile range

The Monte Carlo framework therefore generates a distribution of plausible future electricity price trajectories for each scenario considered. These simulated trajectories constitute the basis for the subsequent analysis by allowing the estimation of reliability option repayments under alternative future market conditions.

The next section presents the simulation outcomes and evaluates the resulting reliability option values and payment gaps across scenarios.

5. Results & Discussion

5.1 Simulation Results

5.1.1 Simulated electricity price dynamics

This section analyses how the different market scenarios affect simulated electricity price dynamics for the 2030 delivery horizon. Since reliability option repayments depend directly on electricity prices exceeding the strike price, understanding the distribution of simulated prices constitutes a first step in the valuation of repayment obligations. Figure 5.1 illustrates the evolution of monthly median simulated electricity prices across scenarios over the 2030 delivery horizon.

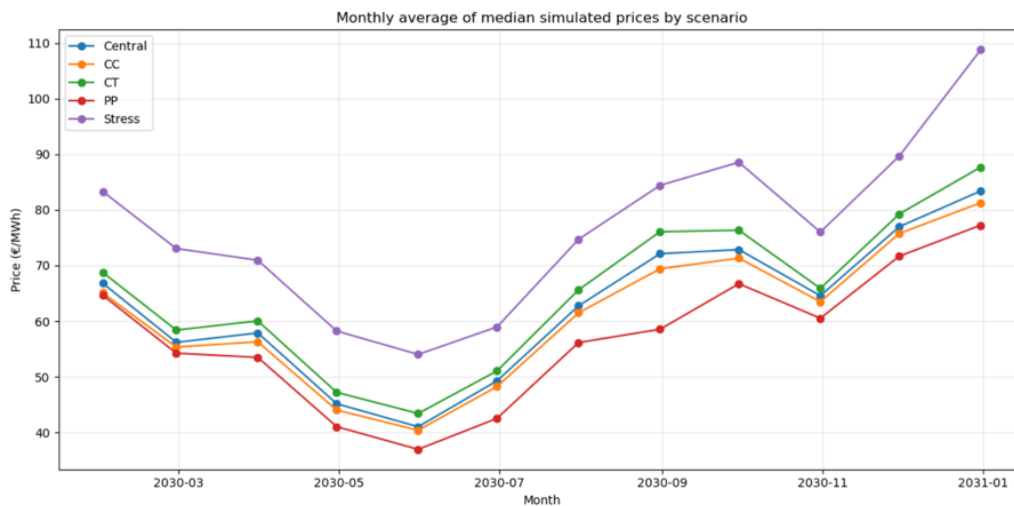


Figure 5.1. Evolution of monthly median simulated electricity prices by scenario

The Stress scenario systematically exhibits the highest simulated price levels, while the Prosumer Power scenario generates lower prices due to stronger renewable penetration and flexibility. The remaining scenarios follow relatively similar seasonal dynamics, although the Constrained Transition scenario displays moderately higher prices during the second half of the year.

Beyond average price trajectories, it is also useful to examine how scenario assumptions affect the dispersion and extreme values of simulated prices. To this end, additional distributional indicators are examined to assess how the overall shape of the simulated price distributions changes across scenarios.

Table 5.1 reports summary statistics of simulated hourly prices for each scenario, including central tendency (mean and median), dispersion (standard deviation), tail indicators (P_5 and P_{95}), and two indicators of extreme outcomes: the share of prices exceeding the strike price and the share of negative prices.

Table 5.1. Summary statistics of simulated electricity prices by scenario

Scenario	Mean price	Median price	Standard deviation	P_5	P_{95}	Share price > strike (%)	Share negative prices (%)
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0	Central	72,42	62,54	75,99	-18,75	223,4	1,81	8,98
1	CC	71,19	61,01	80,17	-27,61	232,5	1,92	11,05
2	CT	79,85	65,12	90,58	-23,96	276,9	3,27	9,99
3	PP	67,87	56,89	92,04	-50,59	253,3	2,46	16,39
4	Stress	102,1	76,94	120,1	-31,98	364,4	7,45	10,65

Source: author's simulations based on ENTSO-E data.

The distributional statistics confirm substantial differences across scenarios. The Stress scenario exhibits the highest average simulated prices (102.10 €/MWh) together with the largest dispersion ($\sigma = 120.10$ €/MWh) and the highest upper tail ($P_{95} = 364$ €/MWh), indicating more frequent extreme price outcomes. In contrast, the Prosumer Power (PP) scenario generates the lowest price levels but the highest share of negative prices (16.39%), reflecting more frequent oversupply situations. Its price dispersion remains relatively high compared with the Central and CC scenarios, likely reflecting greater volatility associated with a higher share of intermittent renewable generation. CC remains close to the central scenario, while CT results in moderately higher prices and a slightly wider upper tail.

5.1.2 Reliability option valuation across scenarios

Building on the simulated electricity price distributions presented above, reliability option repayments were computed for each simulated trajectory using the Belgian CRM strike price of 319 €/MWh.

The table 5.2 summarizes the distribution of simulated RO values across scenarios

Table 5.2. Distribution of simulated reliability option repayments across scenarios

Scenario	Expected RO	Median RO	5th pct	95th pct	Std Dev
Central	12477.91	12387.40	10285.49	15075.34	1434.15
CC	13454.40	13427.59	10930.13	16033.04	1538.55
CT	24962.48	24945.65	21542.43	28507.59	2157.72
PP	18181.56	18091.21	15247.17	21303.58	1875.70
Stress	68690.94	68456.23	61928.10	75908.58	4297.74

Source: author's simulations based on ENTSO-E data.

The results indicate differences in expected repayment obligations across scenarios. The Central and Current Commitments scenarios produce relatively similar RO values, suggesting that the continuation of current energy policies would not significantly alter expected repayments. In contrast, the Constrained Transition and especially the Stress scenario generate significantly larger RO values due to more frequent and more intense high-price episodes exceeding the strike price. Finally, although the Prosumer Power scenario is characterised by lower average prices, it still produces moderately higher RO repayments than the Central scenario, reflecting higher volatility and stronger price polarization rather than sustained scarcity periods.

Figure 5.2 compares the distribution of simulated RO repayments across scenarios with the Belgian CRM Y-4 bid price for the 2030–2031 delivery period. For each scenario, the central line represents the average simulated repayment, while the shaded area corresponds to the interval between the 5th and 95th percentiles. This interval captures the variability of simulated repayment outcomes within each scenario.

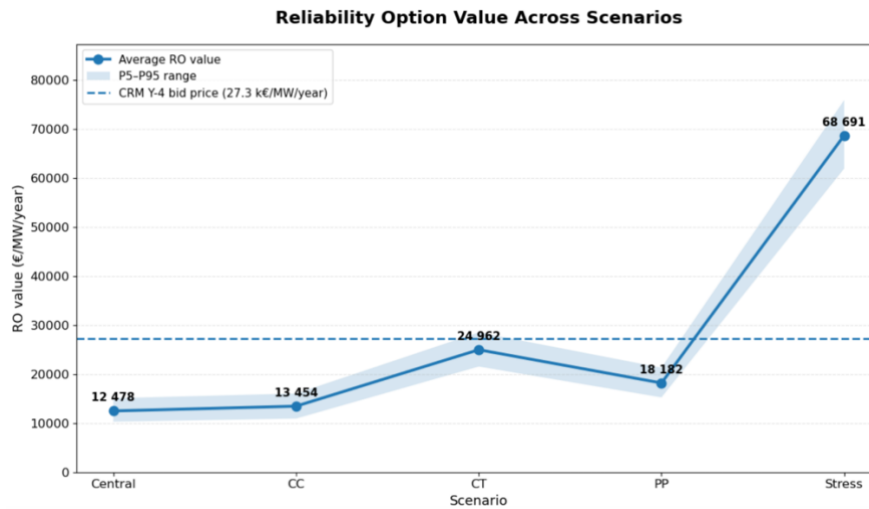


Figure 5.2. Simulated reliability option repayments across scenarios

5.1.3 Payment GAP across scenarios

Figure 5.3 presents the estimated payment gap across scenarios, defined as the difference between the Belgian CRM Y-4 bid price and expected reliability option repayments.

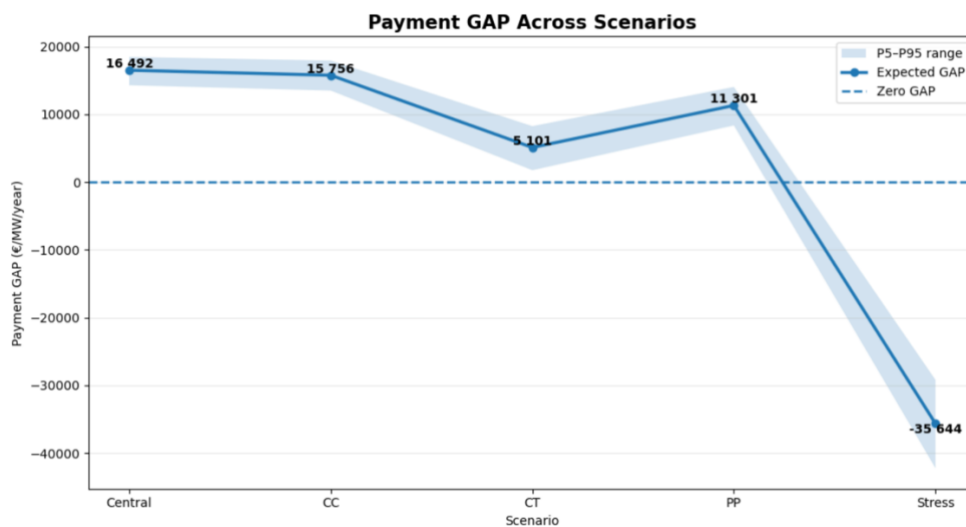


Figure 5.3. Estimated payment gap across scenarios

The estimated payment gap varies across scenarios. The Central and Current Commitments scenarios display relatively large positive gaps, indicating that fixed CRM remuneration would substantially exceed expected repayment obligations under moderate market conditions. The payment gap narrows significantly under the Constrained Transition scenario and becomes strongly negative in the Stress scenario, reflecting the increasing impact of scarcity episodes and high-price events on reliability option repayments. Although the Prosumer Power scenario maintains a positive gap, the reduction relative to the Central scenario suggests that increased price volatility may also affect the effective value retained from CRM remuneration. Overall, these results highlight the sensitivity of the balance between CRM remuneration and reliability option repayments to alternative future electricity market conditions.

5.2 Discussion

5.2.1 Economic interpretation of the payment gap under alternative market conditions

Within the scope of the scenarios and modelling assumptions considered, the results suggest that the relationship between CRM remuneration and reliability option repayments remains relatively stable under moderate market conditions but becomes significantly more sensitive under persistent market stress scenarios. Although three of the four scenarios considered in this study namely, prosumer power, current commitments and constrained transition scenarios differ in their underlying assumptions and electricity price dynamics, these differences remain relatively limited in terms of their impact on expected reliability option repayments. In these scenarios, expected repayments remain below the level of capacity remuneration, resulting in a positive payment gap. By contrast, the regional stress scenario generates repayment levels sufficiently high to exceed the capacity remuneration received.

These findings suggest that the economic value of reliability options repayment is particularly sensitive to prolonged periods of market stress rather than to ordinary market fluctuations. This interpretation is consistent with recent evidence showing that electricity market outcomes can be strongly influenced by external shocks affecting fuel prices, supply conditions, and cross-market volatility transmission (Do et al., 2024). Recent developments in European electricity markets during the COVID-19 period and subsequent energy crisis demonstrated how external shocks may substantially increase electricity price volatility and reshape market dynamics (Stanković et al., 2024).

In addition to uncertainty related to electricity price dynamics, future outcomes may also remain exposed to political and regulatory risks associated with changes in electricity market design, capacity adequacy mechanisms and energy policy frameworks. In particular, differences in the design and coordination of national capacity mechanisms across Europe may affect investment incentives, cross-border electricity flows and regional scarcity conditions, potentially leading to over- or under-procurement of capacity at the European level (Holmberg, 2025). Such dynamics could in turn influence electricity price volatility and the evolution of the payment gap. Consequently, the payment gap may depend not only on expected market fundamentals but also on broader external conditions that remain difficult to anticipate.

5.2.2 Interpreting the payment gap: insights from the simulation results

This analysis does not allow conclusions regarding whether the Belgian CRM over-remunerates capacity providers overall. Capacity remuneration cannot be interpreted solely through expected repayments because the Belgian CRM also aims to provide investment signals, while overall profitability additionally depends on technology-specific investment costs, operating costs and other revenue sources.

The results of this study do suggest however that reliability option repayments does not lead to systematic under-remuneration through the CRM mechanism itself. To illustrate this distinction, and abstracting from investment considerations, a simplified comparison of revenues can be considered. Assuming existing capacity, unchanged production levels, unchanged electricity market revenues and no impact of the CRM on market prices, revenues without participation in the CRM can be expressed as:

$$Revenue_without\ CRM = Spot$$

while revenues associated with participation in the CRM become:

$$\text{Revenue_with CRM} = \text{Spot} + \text{CRM} - \text{RO}$$

Since expected repayments remain below capacity remuneration in most simulated scenarios ($\text{CRM} > \text{RO}$), participation in the CRM appears to remain associated with higher revenues than non-participation under these simplifying assumptions. Therefore, the results do not suggest that participation in the mechanism leaves providers financially worse off through the direct financial flows associated with the CRM itself.

Nevertheless, interpreting these results requires caution because the simplified framework developed in this thesis does not fully reproduce the institutional design of the Belgian reliability option.

5.2.3 Interpreting the payment gap in the broader institutional and market context: the public good dimension of security of supply

In the model, repayment obligations increase mechanically whenever simulated electricity prices exceed the strike price, which may generate highly negative payment gaps under stress conditions.

In reality, such outcomes should not automatically be interpreted as equivalent reductions in the overall revenues of capacity providers. Capacity providers continue to generate revenues through participation in the energy market alongside capacity remuneration, implying that higher repayment obligations do not necessarily translate into lower overall economic returns. Moreover, the Belgian CRM additionally limits downside exposure through a cap on repayment obligations. According to Elia's implementation rules, the total payback obligation cannot exceed the total capacity remuneration received by the contracted Capacity Market Unit (CMU), thereby limiting the extent to which reliability options can erode the value of capacity contracts.

Under this perspective, a positive payment gap should not automatically be interpreted as an economically inefficient transfer toward producers or as evidence of overcompensation. Capacity remuneration is not intended to correspond mechanically to expected repayments but also reflects the value of reducing investor exposure to uncertainty and preserving incentives to maintain or develop reliable capacity. At the same time, reliability options constrain upside outcomes by limiting the ability of producers to fully retain extreme scarcity rents through repayment obligations. The mechanism therefore appears designed to balance consumer protection with the preservation of investment incentives rather than to reproduce a purely market-based remuneration scheme.

This interpretation is consistent with the broader regulatory logic governing European capacity mechanisms. Capacity remuneration mechanisms must demonstrate necessity, proportionality and limitation of excessive support while remaining technologically neutral and limiting costs for consumers. In this sense, security of electricity supply is not treated as a purely market outcome but as a broader public objective that may justify regulatory intervention in order to preserve adequate investment and system reliability (European Commission, 2022).

5.2.4 Capacity mechanisms, flexibility and the energy transition

The *Prosumer Power* scenario highlights a particular dynamic in the interaction between the energy transition and capacity mechanisms. Despite lower average electricity prices resulting from a higher penetration of renewable energy sources, expected repayments associated with reliability options remain relatively elevated. This result can be explained by the higher level of volatility assumed in the scenario: when renewable generation is abundant, low marginal costs exert downward pressure on electricity prices and reduce revenues generated through the energy market. Conversely, during periods of low renewable availability, dispatchable technologies continue to set marginal prices and generate scarcity events during which prices exceed the strike price, thereby increasing the value of reliability option repayments.

In this context, the CRM can be interpreted as a mechanism aimed at maintaining sufficient available capacity to ensure system adequacy during periods when renewable generation is unable to fully meet demand. Reliability options therefore appear to play a dual role: on the one hand, they limit excessive rents that could otherwise be captured during scarcity events through the repayment mechanism; on the other hand, they maintain an additional source of remuneration for resources contributing to security of supply despite potentially lower revenues on the energy market, as illustrated in the *Prosumer Power* scenario.

Importantly, these findings should not be interpreted as suggesting an incompatibility between capacity mechanisms and the expansion of renewable energy. Rather, they illustrate that increasing renewable penetration reduce average electricity prices, but it increases the need for resources capable of responding during periods of low renewable availability. Under current market conditions, this role may still be fulfilled by conventional dispatchable technologies such as gas-fired generation, which explains the outcomes observed in the *Prosumer Power* scenario.

Instead, the broader policy question may not be whether capacity remuneration mechanisms should continue to exist, but rather which forms of flexibility they should encourage. As the electricity system evolves, technologies such as storage, demand response and other flexible resources could progressively fulfil a larger share of the adequacy function currently provided by conventional dispatchable capacity while facilitating the integration of renewable energy. From this perspective, the long-term challenge for capacity mechanisms may be about ensuring that remuneration structures remain aligned with the transition toward a more flexible, sustainable and low-carbon electricity system.

5.2.5 Policy implications for the Belgian reliability option design

Although revenues generated through participation in the spot market were not explicitly modelled in this thesis, the scenario results nevertheless suggest that the design of reliability options may substantially influence repayment dynamics within the Belgian CRM. In particular, the strike price appears to strongly influence repayment dynamics and therefore the economic value associated with capacity contracts.

However, the effect of the strike price should not be interpreted in isolation. The economic attractiveness of reliability options depends on the interaction between the strike price and underlying market conditions, since higher repayment obligations may simultaneously coincide with higher revenues earned on the electricity market. Under this perspective, the calibration of the strike price appears more important than its absolute level.

A strike price set too high relative to market conditions may reduce repayment obligations and weaken the mechanism's ability to recover scarcity rents and limit potential overcompensation.

Conversely, a strike price set too low may trigger frequent repayments and reduce the stabilising effect that capacity remuneration is intended to provide for investment decisions. The effectiveness of the CRM therefore relies on achieving an appropriate balance between consumer protection and preserving investment incentives.

More broadly, these results suggest that the effectiveness of the Belgian CRM depends not only on the existence of reliability options but also on how their parameters are calibrated relative to evolving market conditions. As electricity market dynamics change over time, maintaining an appropriate balance between revenue stabilisation, consumer protection and investment incentives may remain a key challenge for future CRM design.

5.2.6 Limitations of the study

1. Model simplification and abstraction of electricity market dynamics

First, the electricity price model adopted in this thesis remains intentionally simplified and should be interpreted as a reduced-form representation of market dynamics rather than as a full structural electricity market model.

Indeed, although the decomposition framework combining deterministic patterns, an AR(1) stochastic process and a spike component reproduces key stylized characteristics of electricity prices, such as persistence, volatility and extreme events, it does not fully capture the physical and operational complexity of electricity systems.

In particular, the model does not explicitly represent transmission constraints, unit commitment decisions, bidding strategies, reserve activation mechanisms or interactions between energy and balancing markets. More sophisticated electricity price models frequently rely on higher-order autoregressive structures and advanced jump processes to represent extreme price events.

However, the objective of this thesis was not to maximise forecasting accuracy but to generate plausible electricity price trajectories suitable for evaluating the expected financial implications of reliability options.

2. Partial measurement of the economic value of the CRM

Second, the economic value of the Belgian Capacity Remuneration Mechanism (CRM) cannot be reduced to the payment gap estimated in this study.

The payment gap only captures one specific financial dimension of the mechanism, namely the difference between capacity remuneration (represented here by the bid-volume weighted average accepted bid price) and expected repayments generated by reliability options.

Other potentially important sources of economic value such as revenues earned by capacity providers on the spot market, repayment exemptions applicable to certain technologies, and other financial or regulatory characteristics of the mechanism, are not incorporated into the analysis.

Consequently, the estimated payment gap should not be interpreted as a measure of overall profitability or overcompensation of the Belgian CRM.

3. Scenario dependence and calibration uncertainty

Third, several key drivers of future electricity prices are not explicitly modelled but incorporated indirectly through scenario-specific parameter adjustments.

Indeed, variables such as gas prices, CO₂ prices and renewable penetration influence simulated prices through modifications of the deterministic component, volatility and spike structure rather than through an explicit structural representation of market fundamentals.

This approach allows the framework to remain tractable while incorporating plausible future market conditions. However, the results remain sensitive to the assumptions retained for scenario construction and parameter calibration.

More specifically, estimated spike probabilities, volatility levels and price distributions were adjusted to limit the influence of exceptional historical observations and to better reflect expected market conditions by 2030. Although each adjustment was motivated and documented, these calibrations remain modelling assumptions rather than exact forecasts.

The simulated outcomes should therefore be interpreted as indicative estimates conditional on the retained assumptions rather than as precise predictions of future electricity prices.

4. Regulatory uncertainty and external validity

Finally, the Belgian CRM itself remains subject to regulatory evolution.

Future modifications regarding strike prices, repayment exemptions, penalties, auction design or participation rules may alter both the economic value of reliability options and the incentives created by the mechanism.

Accordingly, the conclusions of this thesis should be interpreted within the current institutional framework and assumptions retained for the 2030–2031 delivery period.

6. Conclusion

This thesis originated from a broader question regarding whether the remuneration received by capacity providers remains proportionate to the financial obligations associated with reliability options and whether the mechanism could potentially contribute to situations of over- or under-remuneration of participating capacity.

To explore this question, this thesis estimated the expected payment gap associated with reliability options under alternative future electricity market conditions. Electricity price trajectories were simulated using a Monte Carlo framework and used to estimate expected repayments under four scenarios representing possible developments of the Belgian electricity system for the 2029–2030 delivery period. These expected repayments were then compared with the remuneration obtained through the Belgian CRM (here categorized as the bid-volume weighted average accepted bid price).

The results suggest that expected repayments remain below capacity remuneration under most simulated scenarios and only exceed remuneration under the Regional Stress scenario. Within the simplified framework developed in this thesis, these findings do not suggest that reliability option repayments lead to under-remuneration through the CRM mechanism itself. Under the assumptions of existing capacity, unchanged production levels, unchanged electricity market revenues and no impact of the CRM on market prices, expected repayments remain below capacity remuneration in most scenarios, implying that participation in the CRM does leave providers financially worse off through the direct financial flows associated with the mechanism.

However, extending this interpretation beyond the simulated payment gap requires caution. When considering the broader institutional and market context, the results do not allow conclusions regarding whether the Belgian CRM over-remunerates capacity providers overall. Capacity remuneration cannot be interpreted solely through expected repayments, since the CRM also aims to provide investment signals and support security of supply. Moreover, the overall profitability of participation depends on factors that remain outside the scope of this analysis, including revenues earned on the electricity market, technology-specific capital expenditures, financing conditions, existing support schemes and additional revenue streams.

Finally, this thesis also provides insights into the interaction between capacity mechanisms and the energy transition. The results do not support the idea that capacity mechanisms are incompatible with increasing renewable penetration. Instead, they suggest that while higher shares of renewable generation may reduce average electricity prices, they may simultaneously increase the value of resources capable of responding during periods of low renewable availability. From this perspective, the broader policy question may not necessarily be whether capacity remuneration mechanisms should continue to exist, but rather which forms of flexibility they should encourage. As electricity systems evolve, technologies such as storage, demand response and other flexible resources may progressively provide a larger share of the adequacy function currently fulfilled by conventional dispatchable capacity.

Overall, this thesis suggests that the economic interpretation of the Belgian CRM cannot be reduced to comparing capacity remuneration and expected repayments alone but must also consider broader market conditions and the evolving needs of the electricity system.

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Declaration on the Use of Artificial Intelligence

Artificial intelligence tools were used throughout the preparation of this thesis, particularly to support Python coding tasks, including parameter calibration and the generation of simulations, as well as for language support and improvements in syntax and sentence structure in English.

8. Appendices

Appendix A. OLS regression results for the deterministic component

Table A1. OLS estimation results for the deterministic electricity price component

Variable	Coefficient	Std Error	t-stat	p-value
const	75.943	1.669	45.497	<0.001
h_1	-3.495	1.829	-1.911	0.056
h_2	-5.751	1.829	-3.145	0.002
h_3	-4.131	1.829	-2.259	0.024
h_4	4.040	1.829	2.209	0.027
h_5	15.016	1.829	8.212	<0.001
h_6	23.622	1.829	12.918	<0.001
h_7	24.167	1.829	13.216	<0.001
h_8	19.366	1.829	10.591	<0.001
h_9	12.169	1.829	6.655	<0.001
h_10	5.319	1.829	2.909	0.004
h_11	-0.804	1.829	-0.440	0.660
h_12	-3.983	1.829	-2.178	0.029
h_13	-3.552	1.829	-1.943	0.052
h_14	1.019	1.829	0.557	0.577
h_15	11.415	1.829	6.243	<0.001
h_16	26.226	1.829	14.342	<0.001
h_17	38.963	1.829	21.307	<0.001
h_18	38.395	1.829	20.997	<0.001
h_19	30.949	1.829	16.925	<0.001
h_20	23.965	1.829	13.106	<0.001
h_21	17.244	1.829	9.430	<0.001
h_22	10.942	1.829	5.984	<0.001
h_23	4.182	1.829	2.287	0.022
d_1	3.789	0.988	3.836	<0.001
d_2	3.315	0.988	3.357	<0.001
d_3	2.467	0.988	2.498	0.012
d_4	-0.534	0.987	-0.541	0.589
d_5	-15.407	0.988	-15.599	<0.001
d_6	-23.454	0.988	-23.746	<0.001
m_2	-8.796	1.268	-6.938	<0.001
m_3	-7.191	1.238	-5.807	<0.001
m_4	-20.602	1.269	-16.236	<0.001
m_5	-24.824	1.269	-19.564	<0.001
m_6	-15.588	1.280	-12.179	<0.001
m_7	-3.731	1.269	-2.940	0.003
m_8	10.789	1.269	8.503	<0.001
m_9	9.240	1.280	7.219	<0.001
m_10	-1.361	1.269	-1.073	0.283
m_11	12.411	1.280	9.697	<0.001
m_12	19.279	1.269	15.194	<0.001

Source: Author's calculations in Python based on historical price data.

This table reports the estimated coefficients of the deterministic component regression, including hourly, daily and monthly calendar effects.

Appendix B. Diagnostic analysis of the 2022 price regime

To assess whether 2022 represented an atypical price regime likely to influence the deterministic baseline, descriptive statistics were computed separately for 2022 and for the remaining years of the historical sample.

Table B1. Comparison of electricity price statistics between 2022 and the remaining historical sample

Price statistics/ Years	2022	Remaining years
Mean electricity price (€/MWh)	244.52	63.36
Standard deviation (€/MWh)	134.67	48
Minimum electricity price (€/MWh)	-100	-500
Maximum electricity price (€/MWh)	871	696.02

Source: Author's calculations in Python based on historical price data.

The results confirm that 2022 exhibits different price level compared with the rest of the historical sample, supporting the re-centering of the deterministic baseline.

Appendix C. Sensitivity of calendar effects to individual years

To assess whether the influence of 2022 on estimated calendar effects is exceptional or reflects a broader sensitivity of the model to individual years, the deterministic regression was re-estimated after excluding selected years (2022 and 2020). The resulting calendar coefficients were compared with those obtained under the baseline specification estimated on the full historical sample.

Table C1. Sensitivity of estimated calendar coefficients to excluding individual years

Excluded year	Average coefficient change (€/MWh)	Most affected coefficient	Largest coefficient change (€/MWh)
2022	4.33	m_8	28.36
2025	2.17	m_9	6.08
2021	2.14	m_12	18.31
2023	1.45	m_12	8.39
2017	1.38	m_8	5.96
2019	1.21	m_12	4.98
2018	1.15	const	5.06
2016	0.91	const	4.92
2020	0.87	const	4.36
2026	0.83	const	2.64
2024	0.7	m_8	2.65

Source: Author's calculations in Python based on historical price data.

The sensitivity analysis indicates that excluding 2022 produces the largest changes in estimated calendar coefficients among all years considered, with an average absolute coefficient difference of **4.33 €/MWh**. This suggests that 2022 had a stronger influence on the estimated temporal structure than other individual years.

However, other individual years also affect the estimated temporal structure to some extent (for example, excluding 2025 and 2021 results in average absolute coefficient differences of **2.17 €/MWh** and **2.14 €/MWh**, respectively), indicating that estimated calendar effects are influenced by information contributed by multiple historical years and not exclusively by the exceptional conditions observed in 2022.

Similarly, while excluding 2022 produces the largest individual coefficient change (August: 28.36 €/MWh), other years also affect specific calendar effects (for example, excluding 2021 substantially modifies the December effect: 18.31 €/MWh).

Consequently, excluding individual years was not retained as the preferred approach. Instead, the baseline specification preserves the full historical sample and only adjusts the average deterministic level through re-centering.

Appendix D. Sensitivity analysis of the spike probability smoothing parameter

Table D1. Sensitivity analysis of spike probability smoothing specifications

Spec	Smooth	Include 2022	Avg positive spike probability	Variation across positive cells	Max positive spike probability	Avg negative spike probability	Variation across negative cells	Max negative spike probability	Robust positive cells	Robust negative cells
S1	None	Yes	0.050258928	0.035289839	0.138709677	0.050358585	0.067804488	0.361290323	78	211
S2	$\alpha = 0.3$	Yes	0.052275294	0.014437562	0.112098106	0.05927028	0.043135926	0.267904558	78	211
S3	$\alpha = 0.5$	Yes	0.051626479	0.010312544	0.094357059	0.056622897	0.030811376	0.205647382	78	211
S4	$\alpha = 0.7$	Yes	0.050977664	0.006187527	0.076616012	0.053975515	0.018486826	0.143390205	78	211
S5	$\alpha = 0.9$	Yes	0.050328848	0.002062509	0.058874965	0.051328132	0.006162275	0.081133029	78	211
S6	$\alpha = 0.7$	No	0.007565981	0.004076063	0.034614325	0.05795057	0.020260588	0.157878455	23	207

Source: Author's calculations in Python based on historical price data.

Table D1 shows that increasing α progressively reduces the dispersion of hour-month spike probabilities and limits extreme local estimates. Without smoothing (S1), probabilities remain highly heterogeneous across cells, suggesting potential overfitting to isolated historical observations. Conversely, strong smoothing ($\alpha = 0.9$) substantially compresses the distribution of spike probabilities and risks removing seasonal information.

The choice of $\alpha = 0.7$ is motivated by the strong influence of crisis-period observations on local spike probabilities. Sensitivity analysis shows that excluding 2022 reduces the number of robust positive hour-month cells from 78 to 23, suggesting that part of the observed spike structure is driven by exceptional market conditions. Rather than excluding these observations entirely, the smoothing procedure gives greater weight to the global spike frequency while preserving local seasonal information where sufficient historical support exists.

Appendix E. Robustness check of negative spike magnitudes to yearly exclusion

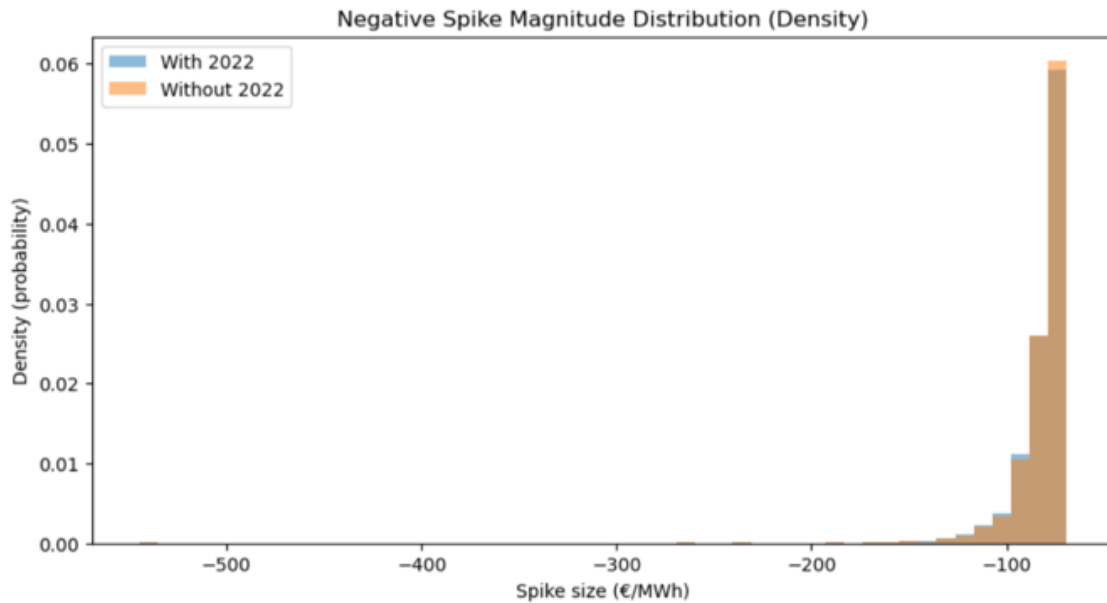


Figure E1. Distribution of negative spike magnitudes with and without 2022

Figure E1 compares the distribution of negative spike magnitudes with and without the inclusion of 2022, which was selected because it represents one of the years with the strongest influence on spike behaviour in previous robustness checks. The distributions remain almost unchanged, suggesting that negative spike magnitudes are relatively insensitive to yearly composition effects.

Appendix F. Robustness analysis across alternative price process specifications

To evaluate whether the methodological adjustments introduced in the electricity price process materially affect simulation outcomes, alternative model specifications are compared. Since the deterministic, stochastic and spike components jointly define the historical price process, the objective is not to remove model components but rather to assess the impact of the adjustments applied to each component. Table F1 reports the resulting price characteristics and expected reliability option repayments under each specification.

Table F1. Robustness analysis across alternative price process specifications

Spec	Deterministic component	Normal component	Spike occurrence	Spike magnitude	Mean price	Std price	P95 price	Hours > K (%)	Expected RO	Median RO	P5 RO	P95 RO	Mean hours > K	Interpretation	Δ RO vs final (%)
M0	Original μ	Included, unchanged	Baseline	Baseline	92.200	83.260	245.700	3.110	29342.420	29247.920	25384.870	33576.020	272.020	Unadjusted price process	134.800
M1	Adjusted μ	Included, unchanged	Baseline	Baseline	74.580	83.260	228.090	2.710	24857.910	24733.250	21274.730	28749.880	237.540	Effect of mean re-centering	98.910
M2	Adjusted μ	Included, unchanged	Adjusted	Baseline	74.560	84.140	232.340	2.750	25228.100	25207.460	21531.800	29108.670	240.630	Effect of spike occurrence adjustment	101.870

M3	Adjusted μ	Included, unchanged	Baseline	Adjusted	72.570	75.390	220.900	1.820	12566.130	12451.670	10267.830	14961.840	159.480	Effect of spike magnitude adjustment	0.550
M4	Adjusted μ	Included, unchanged	Adjusted	Adjusted	72.430	76.000	223.600	1.810	12496.900	12478.080	10295.280	14984.100	158.280	Final specification	0.000

Source: Author's simulations in Python based on historical price data.

The specification robustness analysis reveals that adjustments to spike magnitudes have a substantially larger impact on expected reliability option repayments than adjustments to spike occurrence probabilities. While modifying spike occurrence leads to relatively limited changes in expected repayments, adjusting spike magnitudes reduces expected repayments considerably. This result is consistent with the structure of reliability options, whose repayments depend directly on the size of price exceedances above the strike price rather than only on their frequency. Consequently, changes affecting the upper tail of the price distribution translate into large differences in expected repayments.

Although the magnitude adjustment materially changes model outcomes, this does not necessarily imply that the specification is inappropriate. Instead, the results indicate that repayment estimates are highly sensitive to assumptions regarding spike magnitudes and suggest that the original specification may have placed excessive weight on specific historical observations, particularly 2016, in determining extreme price events. The final specification is nevertheless retained because it limits the disproportionate influence of individual historical years on extreme price outcomes while preserving the broader historical structure of electricity prices. Since additional scenarios are subsequently imposed on simulated trajectories, the objective is to maintain a relatively neutral baseline specification rather than embedding extreme assumptions directly into the historical specification.

Table F2. Contribution of individual price process components

Spec	Price process	Mean price	Std price	P95 price	Hours > K (%)	Expected RO	Median RO	P5 RO	P95 RO	Mean hours > K	Interpretation
Historical	Observed prices	80.98	82	240.55	2.64	259531	259531	259531	259531	2380	Historical reference
P1	$P = \mu$	63.51	21.3	98.51	0	0	0	0	0	0	Deterministic seasonality only
P2	$P = \mu + X$	63.52	48.6	141.17	0.02	47.83	12.91	0	223.5	1.71	Adds normal stochastic persistence
P3	$P = \mu + X + J$	72.43	76	223.6	1.81	12496.9	12478.1	10295.3	14984.1	158.28	Full decomposition

Source: Author's simulations in Python based on historical price data.

Table F2 decomposes the contribution of the different price process components to simulated electricity price dynamics and reliability option repayments. The deterministic component alone (*P1*) reproduces seasonal average price patterns but generates no scarcity episodes or reliability option repayments, since prices never exceed the strike price. Adding the stochastic

autoregressive component ($P2$) increases price dispersion and introduces limited high-price events, resulting in small but non-zero expected repayments. The inclusion of the spike component ($P3$) substantially increases upper-tail price behaviour, hours above the strike price, and expected reliability option repayments, demonstrating that extreme price events are the primary driver of reliability option obligations in the model.

Appendix G. Monte Carlo convergence analysis

Table G1. Sensitivity of estimated RO repayments to the number of Monte Carlo trajectories

N	Expected RO (CC)	CC - Δ vs 1000	CC - Δ (%)	Expected RO (Stress)	Stress - Δ vs 1000	Stress - Δ (%)
200	13267.11	-121.168	-0.905	68496.252	144.897	0.212
500	13396.558	8.28	0.062	68643.783	292.428	0.428
1000	13388.277	0	0	68351.354	0	0
2000	13395.001	6.724	0.05	68439.815	88.461	0.129
5000	13380.29	-7.987	-0.06	68514.775	163.421	0.239

Source: Author's simulations in Python based on historical price data.

Results indicate that increasing the number of trajectories beyond 1,000 does not materially affect the estimated expected reliability option repayment. In the CC scenario, deviations relative to the 1,000-trajectory benchmark remain below 0.1% once at least 500 simulations are used. Similar stability is observed under the Stress scenario, despite its higher volatility, where deviations remain below 0.5%. These results suggest that the Monte Carlo estimates have effectively converged around 1,000 trajectories.

Appendix H. Scenario calibration

General calibration methodology

This annex presents the parameter adjustments applied to the baseline electricity price model in order to represent the alternative electricity market scenarios considered for 2030. Starting from the model calibrated on historical Belgian day-ahead prices (2016–2026), scenario-specific modifications are introduced to the deterministic component (μ), volatility (σ), and spike process parameters.

These adjustments are not intended to reproduce exact future prices but to generate internally coherent market conditions for the simulations. For each scenario, the resulting average price is reconstructed by combining the calibrated deterministic component and the adjusted spike parameters and is then compared with the expected average price range reported in Elia's *Adequacy and Flexibility* study for the corresponding scenario as a plausibility check of the calibration.

Baseline Scenario (historical data)

This central scenario is based on historical data over the period 2016–2026 and captures the main dynamics of the Belgian electricity market. It is considered a realistic approximation of a power system combining thermal generation (gas), CO₂ costs and an increasing share of renewable energy, and serves as a reference framework from which the other scenarios are derived.

Analyses published by Elia indicate that future price levels should remain broadly comparable on average, without any major structural break. In particular, Figure 10-53 of the *Adequacy &*

Flexibility report shows that simulated average prices over the 2027–2037 horizon remain within a range of approximately 60 to 80 €/MWh.

This estimate is consistent with the levels observed in our baseline model, whose average price amounts to **72.14 €/MWh**. This average price is composed of an average structural component μ_t of **63.5 €/MWh**, to which the net effect of spikes of **+8.59 €/MWh** is added (namely +12.43 €/MWh from positive spikes and -3.84 €/MWh from negative spikes).

The central scenario therefore provides a robust and coherent basis for the prospective analysis, ensuring continuity between historical observations and future projections.

Current Commitments & Ambitions (CC)

1) Scenario description

This scenario corresponds to the trajectory currently being followed by Belgium, assuming that the announced energy policies and objectives are effectively implemented. It is notably based on the ambitions of the National Energy and Climate Plan (NECP), recent governmental agreements, and electrification projections.

Within this framework, the electricity system evolves towards a growing share of renewable energy sources, particularly photovoltaics, in line with European and national objectives. However, as highlighted by Elia, the development of flexibility, especially on the demand side (EVs, residential batteries, DSR), remains slower than expected.

2) Adjustment of μ

The average variation is obtained by weighting the hourly effects. This approach allows to adjust the deterministic component μ , which represents the expected price level based on calendar and intra-day effects.

Step 1: Assumptions and calibration choices

Several candidate values were considered in order to avoid selecting a single adjustment without testing. The selected values correspond to the central calibration judged most consistent with the qualitative scenario assumptions.

Table H1. Candidate calibrations and weighted contributions used to adjust the deterministic component (μ) in the Current Commitments scenario

Expected mechanism	Assumption	Candidate calibration	Hours/day	Weighted contribution
More solar generation creates more oversupply during midday	Conservative	-2 €/MWh	7	-0.58
	Moderate (selected)	-4.5 €/MWh	7	-1.31
	Strong	-7 €/MWh	7	-2.04
Evening flexibility partially mitigates scarcity	Conservative	+1 €/MWh	4	0.17
	Moderate (selected)	+2 €/MWh	4	0.33
	Strong	+4 €/MWh	4	0.67
Remaining hours	No adjustment	0	13	0

Step 2: Detail of the main calculation

Reporting all calculations would be too cumbersome; therefore, only the detailed calculation of the final selected value is presented, while the other candidate values follow the same calculation approach.

Time assumptions:

- Solar hours: 10 a.m. to 4 p.m., i.e. 7 hours per day
- Evening hours: 6 p.m. to 9 p.m., i.e. 4 hours per day
- Other hours: 13 hours per day

Applied effects:

1. Solar effect ≈ -4.5 €/MWh: justified by the increase in photovoltaic generation, which leads to lower prices during hours of high production due to excess supply.
2. Evening effect $\approx +2$ €/MWh: evening price increases remain limited thanks to the gradual development of flexibility solutions (batteries, demand-side response), which mitigate demand peaks.
3. Other hours = 0

Calculation :

$$\Delta\mu_{average} = \left(-4.5 \times \frac{7}{24}\right) + \left(2 \times \frac{4}{24}\right) + \left(0 \times \frac{13}{24}\right)$$

$$\Delta\mu_{average} = -1.31 + 0.33 = -0.98 \text{ €/MWh}$$

This scenario therefore applies a **shift of -0.98 €/MWh** to the μ_t of the central scenario.

3) Adjustment of the **spike component (J)**

Step 1: Assumptions and calibration choices

Spike calibration was performed by modifying either the frequency or the intensity of extreme events (or both) relative to the baseline process.

Table H2. Candidate calibrations and selected adjustments for spike probabilities and magnitudes in the Current Commitments scenario

Component	Expected mechanism	Evidence / assumption	Candidate values	Selected	Applied calculation
Positive spike probability	Scarcity remains possible	Gas still occasionally marginal	$\times 1.00$ / $\times 1.05$ / $\times 1.10$	$\times 1.05$	$p^+ = p_{\text{base}^+} \times 1.05$
Positive spike magnitude	No strong increase in intensity	Average prices remains stable in CC	$\times 1.00$	$\times 1.00$	$M^+ = M_{\text{base}^+} \times 1$
Negative spike probability	More oversupply situations	Elia shows that the number of low-price hours, defined as prices below 5 €/MWh, increases in the CC scenario from 2030 onwards and reaches a peak around 2032 (Section 10.5.2, Figure 10-35)	$\times 1.20$ / $\times 1.30$	$\times 1.20$	$p^- = p_{\text{base}^-} \times 1.20$

Negative spike magnitude	Events become more frequent than severe	Conservative assumption	$\times 1.00 / \times 1.05 / \times 1.10$	$\times 1.05$	$M^- = M_{\text{base}}^- \times 1.05$
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Step 2: Detail of the main calculation

Starting from the values of the central scenario:

- Average positive spikes = +12.43 €/MWh
- Average negative spikes = -3.84 €/MWh

Calculation :

Positive spikes :

$$\text{Positive spikes CC} = 12.43 \times 1.05 \times 1.00 = 13 \text{ €/MWh}$$

Negative spikes :

$$\text{Negative spikes CC} = -3.84 \times 1.20 \times 1.05 = -4.84 \text{ €/MWh}$$

Net spikes effect :

$$\text{Net spikes effect CC} = 13 - 4.84 = +8.16 \text{ €/MWh}$$

The net effect of spikes in the CC scenario therefore remains positive, but decreases slightly relative to the central scenario.

Positive spikes increase only marginally, rising from +12.43 to +13 €/MWh, while negative spikes increase more significantly in absolute value, from -3.84 to -4.84 €/MWh.

The net spike effect therefore becomes +8.16 €/MWh, compared with +8.59 €/MWh in the central scenario, corresponding to a decrease of approximately **-0.37 €/MWh**.

4) Adjustment of volatility σ

Volatility does not directly intervene in the calculation of the average price presented below, since the normal component X_t is centred around zero. It therefore does not affect the average price level, but only the amplitude of fluctuations around μ_t depending on the scenario. Its adjustment is taken into account in the Monte Carlo simulations, where it influences the dispersion of price trajectories rather than their average. For this scenario, we apply:

Baseline σ x 1.10 to reflect moderate renewable penetration.

5) Final calibrated parameter set & Consistency check

Table H3. Final calibrated parameter set for the Current Commitments scenario

Parameter	Adjustment
$\Delta\mu$	-0.98 €/MWh
Net spike effect	+8.16€/MWh
Positive probability	$\times 1.05$
Positive magnitude	$\times 1.00$
Negative probability	$\times 1.20$
Negative magnitude	$\times 1.05$
Volatility	$\times 1.10$

Consistency check: reconstruction of the average price

To assess whether the calibrated parameter set produces plausible outcomes, the average price obtained under the simulated CC scenario is reconstructed and compared with the average price level expected by Elia for a comparable trajectory.

The objective of this consistency check is not to reproduce Elia's projections exactly, but to verify that the calibrated parameters lead to a simulated average price that remains within a realistic and coherent range.

By combining the deterministic component and the spikes:

$$P_{CC\text{average}} = 63.5 - 0.98 + 8.16 = 70.68 \text{ €/MWh}$$

$$P_{CC\text{average}} \approx \mathbf{70.7 \text{ €/MWh}}$$

The CC scenario therefore leads to an average price that is **1.44 €/MWh lower** than our central scenario. This result is consistent with the nature of the CC scenario, which extends the current trajectory of the Belgian electricity system, characterised by a gradual increase in renewable generation without any major structural break.

Constrained Transition (CT)

1) Scenario description

This scenario reflects a slowdown in the energy transition, with limited development of renewable energy sources, flexibility, and electrification. The system remains more dependent on thermal generation, which limits daytime price reductions and increases tensions during critical periods.

However, this increase is partially offset by lower demand resulting from more limited electrification.

2) Adjustment of μ

Step 1: Assumptions and calibration choices

Table H4. Candidate calibrations and weighted contributions used to adjust the deterministic component (μ) in the Constrained Transition scenario

Expected mechanism	Assumption	Candidate calibration	Hours/day	Weighted contribution
Lower renewable penetration limits midday price reductions	Conservative	-1 €/MWh	7	-0.29
	Moderate (selected)	-2 €/MWh	7	-0.58
	Strong	-4.5 €/MWh	7	-1.31
Greater thermal dependence and lower flexibility increase evening tensions	Conservative	+5 €/MWh	4	+0.83

	Moderate (selected)	+10 €/MWh	4	+1.67
	Strong	+15 €/MWh	4	+2.50
Remaining hours	No adjustment	0	13	0

Step 2: Detail of the main calculation

Time assumptions:

- Solar hours: 10 a.m. to 4 p.m., i.e. 7 hours per day
- Evening hours: 6 p.m. to 9 p.m., i.e. 4 hours per day
- Other hours: 13 hours per day

Applied effects :

1. Solar effect ≈ -2 €/MWh: weaker effect than in the CC scenario due to lower renewable penetration.
2. Evening/winter effect $\approx +10$ €/MWh: increased tensions during critical periods (less flexibility, greater thermal dependence).
3. Other hours = 0: price increases are mainly concentrated during critical periods.

Calculation :

$$\Delta\mu_{average} = \left(-2 \times \frac{7}{24}\right) + \left(10 \times \frac{4}{24}\right)$$

$$\Delta\mu_{average} = -0.58 + 1.67 = +1.09 \text{ €/MWh}$$

This scenario therefore applies an adjustment of **+1.09 €/MWh** to the deterministic component μ .

3) Adjustment of the **spike component** (J)

Step 1: Assumptions and calibration choices

Table H5. Candidate calibrations and selected adjustments for spike probabilities and magnitudes in the Constrained Transition scenario

Component	Expected mechanism	Evidence / assumption	Candidate values	Selected	Applied calculation
Positive spike probability	Scarcity events become more frequent	Lower renewable penetration increases situations where thermal generation sets the price	$\times 1.10 / \times 1.20 / \times 1.30$	$\times 1.30$	$p^+ = p^+_{\text{base}} \times 1.30$
Positive spike magnitude	Higher scarcity leads to stronger upward price movements	Slight increase in spike intensity due to system stress	$\times 1.00 / \times 1.05 / \times 1.10$	$\times 1.10$	$M^+ = M^+_{\text{base}} \times 1.10$
Negative spike probability	Fewer oversupply situations	Lower renewable penetration reduces occurrence of very low-price hours	$\times 0.80 / \times 0.90 / \times 1.00$	$\times 0.80$	$p^- = p^-_{\text{base}} \times 0.80$
Negative spike magnitude	Less severe negative prices	Conservative assumption	$\times 0.90 / \times 0.95 / \times 1.00$	$\times 0.95$	$M^- = M^-_{\text{base}} \times 0.95$

Step 2: Detail of the main calculation

Starting from the values of the central scenario:

- Average positive spikes = +12.43 €/MWh
- Average negative spikes = -3.84 €/MWh

Calculation :

Positive spikes :

$$12.43 \times 1.30 \times 1.10 = 17.8 \text{ €/MWh}$$

Negative spikes :

$$-3.84 \times 0.80 \times 0.95 = -2.91 \text{ €/MWh}$$

Net effect :

$$17.8 - 2.91 = +14.9 \text{ €/MWh}$$

The net effect of spikes therefore increases significantly relative to the central scenario.

Positive spikes become both more frequent and more intense, while negative spikes decrease in both frequency and magnitude. This reflects a more constrained system in which stress periods dominate.

4) Adjustment of volatility σ

Baseline σ x 1.15 to reflect a lower adaptation capacity of the system.

5) Final calibrated parameter set & Consistency check

Table H6. Final calibrated parameter set for the Constrained Transitino scenario

Parameter	Adjustment
$\Delta\mu$	-1.09 €/MWh
Net spike effect	+14.9€/MWh
Positive probability	×1.30
Positive magnitude	×1.10
Negative probability	×0.80
Negative magnitude	×0.95
Volatility	×1.15

Consistency check: reconstruction of the average price

By combining the deterministic component and the spikes:

$$P_{CT} = 63.5 + 1.09 + 14.9 = 79.49 \text{ €/MWh}$$

$$P_{CT} \approx \mathbf{79.5 \text{ €/MWh}}$$

The CT scenario therefore leads to an average price higher than in the CC scenario, with a difference of approximately **8.5 €/MWh**. This result is consistent with Elia's conclusions (*Adequacy & Flexibility*), whose Figure 10-53 highlights a gap of **around 5 to 10 €/MWh** between the CT scenario and the CC and PP scenarios.

Prosumer Power (PP)

1) Scenario description

This scenario represents a strong adoption of decentralised technologies, notably residential photovoltaics, home batteries, and electric vehicles. It corresponds to a highly electrified energy system in which consumers become active market participants (prosumers).

Within this framework, renewable generation, particularly solar power, increases significantly, leading to numerous oversupply situations during daytime hours. At the same time, the development of flexibility (storage, demand-side management) partially mitigates evening stress periods, although it does not eliminate them entirely.

The system is therefore characterised by strong intra-day variability, with very low prices during daytime hours and higher price levels during periods without renewable generation.

2) Adjustment of μ

Step 1: Assumptions and calibration choices

Unlike the previous scenarios, the PP scenario introduces seasonal differentiation in the deterministic component in order to capture stronger intra-annual variability associated with renewable penetration and changing residual demand patterns.

Table H7. Seasonal calibration of deterministic component (μ) adjustments in the Prosumer Power scenario

Season	Solar hours (7h/day)	Evening hours (4h/day)	Other hours (13h/day)	Seasonal average
Summer	-16.2 €/MWh	+2 €/MWh	-3 €/MWh	-6.01 €/MWh
Spring / Autumn	-10 €/MWh	+3 €/MWh	-2 €/MWh	-3.50 €/MWh
Winter	-5 €/MWh	+5 €/MWh	-1 €/MWh	-1.17 €/MWh

Table H8. Annual aggregation of seasonal deterministic adjustments in the Prosumer Power scenario

Season	Seasonal adjustment	Weight (days/year)	Weighted contribution
Summer	-6.01 €/MWh	153/365	-2.52
Spring / Autumn	-3.50 €/MWh	92/365	-0.88
Winter	-1.17 €/MWh	120/365	-0.38
Annual average adjustment			-3.79 €/MWh

Step 2: Detail of the main calculation

Time assumptions:

- Solar hours: 10 a.m. to 4 p.m., i.e. 7 hours per day
- Evening hours: 6 p.m. to 9 p.m., i.e. 4 hours per day
- Other hours: 13 hours per day

Applied effects :

1. Solar effect = -16 / -5 €/MWh: strong price reduction linked to the numerous oversupply hours.

2. Evening effect = +2 / +5 €/MWh: moderate evening tensions despite the development of flexibility.
3. Other hours = -3 / -1 €/MWh: unlike the other scenarios, where adjustments mainly concentrate on critical hours, the PP scenario introduces a more generalised effect across the entire day. This reflects a structural decrease in the overall price level linked to lower dependence on thermal generation.

The average effect is calculated for each season.

Summer :

$$\Delta\mu_{summer} = (-16.2 \times 7/24) + (2 \times 4/24) + (-3 \times 13/24)$$

$$\Delta\mu_{summer} = -6.01 \text{ €/MWh}$$

Spring / autumn :

$$\Delta\mu_{inter} = (-10 \times 7/24) + (3 \times 4/24) + (-2 \times 13/24)$$

$$\Delta\mu_{inter} = -3.50 \text{ €/MWh}$$

Winter :

$$\Delta\mu_{winter} = (-5 \times 7/24) + (5 \times 4/24) + (-1 \times 13/24)$$

$$\Delta\mu_{winter} = -1.17 \text{ €/MWh}$$

The annual average effect is then obtained by weighting these seasonal effects according to the number of days in each period :

$$\Delta\mu_{average} = (153/365 \times -6.01) + (92/365 \times -3.50) + (120/365 \times -1.17)$$

$$\Delta\mu_{average} \approx -3.79 \frac{\text{€}}{\text{MWh}}$$

This scenario therefore applies an adjustment of **-3.79 €/MWh** to the deterministic component μ .

3) Adjustment of the **spike component** (J)

Step 1: Assumptions and calibration choices

Table H9. Candidate calibrations and selected adjustments for spike probabilities and magnitudes in the Prosumer Power scenario

Component	Expected mechanism	Evidence / assumption	Candidate values	Selected	Applied calculation
Positive spike probability	Evening scarcity events remain present	Even with higher renewable penetration, evening ramps may still occur when solar generation declines	$\times 1.00$ / $\times 1.10$ / $\times 1.15$	$\times 1.15$	$p^+ = p^+_{base} \times 1.15$
Positive spike magnitude	Slightly stronger upward price movements	Residual thermal dependence during evening hours can still create positive price spikes	$\times 1.00$ / $\times 1.05$ / $\times 1.10$	$\times 1.05$	$M^+ = M^+_{base} \times 1.05$

Negative spike probability	Oversupply situations become much more frequent. Higher photovoltaic generation increases the number of low-price and negative-price hours.	Figure 10-37 (Elia Adequacy & Flexibility) notably confirms a significant increase in the number of hours with prices below 5 €/MWh in the PP scenario	$\times 1.30 / \times 1.50 / \times 1.70$	$\times 1.70$	$p^- = p^-_{\text{base}} \times 1.70$
Negative spike magnitude	Negative prices become more intense	Strong renewable generation during low-demand hours increases downward price pressure	$\times 1.05 / \times 1.10 / \times 1.15$	$\times 1.15$	$M^- = M^-_{\text{base}} \times 1.15$

Step 2: Detail of the main calculation

Starting from the values of the central scenario:

- Average positive spikes = +12.43 €/MWh
- Average negative spikes = -3.84 €/MWh

Calculation :

Positive spikes :

$$12.43 \times 1.15 \times 1.05 = 15 \text{ €/MWh}$$

Negative spikes :

$$-3.83 \times 1.70 \times 1.15 = -7.49 \text{ €/MWh}$$

Net effect :

$$15 - 7.49 = +7.51 \text{ €/MWh}$$

Negative spikes increase significantly both in frequency and intensity, reflecting the numerous oversupply situations linked to photovoltaic generation. At the same time, positive spikes remain present during evening ramps. These opposing effects partially offset each other: on the one hand, prices are strongly pushed downward during hours of high solar generation, while on the other hand, they remain elevated during periods without renewable generation. Indeed, despite a globally lower use of gas, gas-fired generation continues to set the price during critical hours, while demand increases due to electrification.

As a result, the overall impact on the average price remains limited.

4) Adjustment of volatility σ

Baseline $\sigma \times 1.35$ to reflect strong variability linked to renewable generation.

5) Final calibrated parameter set & Consistency check

Table H10. Final calibrated parameter set for the Constrained Transition scenario

Parameter	Adjustment
$\Delta\mu$	-3.79 €/MWh
Net spike effect	+7.51€/MWh

Positive probability	×1.15
Positive magnitude	×1.05
Negative probability	×1.70
Negative magnitude	×1.15
Volatility	×1.35

Consistency check: reconstruction of the average price

By combining the deterministic component and the spikes:

$$P_{PP} = 63.5 - 3.79 + 7.51 = 67.22 \text{ €/MWh}$$

$$P_{PP} \approx \mathbf{67.2 \text{ €/MWh}}$$

The PP scenario therefore leads to an average price that is slightly lower but still close to the CC scenario, which is consistent with Elia's results (*Adequacy & Flexibility*), whose Figure 10-53 shows that average price levels remain broadly similar between these two scenarios in particular.

Regional stress / Adequacy stress

1) Scenario description

This scenario corresponds to a stress situation affecting the electricity system, combining several systemic risks: limitations on imports, reduced availability of the French nuclear fleet, low renewable generation, and network constraints.

Within this framework, the system becomes highly dependent on thermal generation capacities, particularly gas-fired plants, which set the market price during a large number of hours.

2) Adjustment of μ

Step 1: Assumptions and calibration choices

The Stress scenario also introduces seasonal differentiation in the deterministic component, as system tensions are expected to be stronger during winter and evening peak periods. The adjustment is therefore higher in winter and during evening hours, reflecting increased dependence on thermal generation and imports under stressed system conditions.

Table H11. Seasonal calibration of deterministic component (μ) adjustments in the Stress scenario

Season	Solar hours (7h/day)	Evening hours (4h/day)	Other hours (13h/day)	Seasonal average
Summer	+1 €/MWh	+17 €/MWh	+5 €/MWh	+5.83 €/MWh
Spring / Autumn	+4 €/MWh	+24 €/MWh	+8 €/MWh	+9.50 €/MWh
Winter	+9 €/MWh	+34 €/MWh	+11 €/MWh	+14.25 €/MWh

Table H12. Annual aggregation of seasonal deterministic adjustments in the Stress scenario

Season	Seasonal adjustment	Weight (days/year)	Weighted contribution
Summer	+5.83 €/MWh	153/365	+2.44
Spring / Autumn	+9.50 €/MWh	92/365	+2.39

Winter	+14.25 €/MWh	120/365	+4.68
Annual average adjustment			+9.51 €/MWh

Step 2: Detail of the main calculation

Time assumptions:

- Solar hours: 10 a.m. to 4 p.m., i.e. 7 hours per day
- Evening hours: 6 p.m. to 9 p.m., i.e. 4 hours per day
- Other hours: 13 hours per day

Applied effects:

1. Solar effect $\approx +1$ to $+9$ €/MWh: limited impact linked to lower renewable generation.
2. Evening effect $\approx +17$ to $+34$ €/MWh: critical periods become highly stressed due to simultaneous constraints on supply and import capacities, increasing the reliance on thermal generation during peak hours.
3. Other hours $\approx +5$ to $+11$ €/MWh: in this scenario, the adjustments are more diffuse and apply across all hours, while remaining more pronounced during critical periods.

The average effect is calculated for each season.

Summer :

$$\Delta\mu_{summer} = (1 \times 7/24) + (17 \times 4/24) + (5 \times 13/24)$$

$$\Delta\mu_{summer} = 5.83 \text{ €/MWh}$$

Spring / Autumn :

$$\Delta\mu_{inter} = (4 \times 7/24) + (24 \times 4/24) + (8 \times 13/24)$$

$$\Delta\mu_{inter} = 9.50 \text{ €/MWh}$$

Winter :

$$\Delta\mu_{winter} = (9 \times 7/24) + (34 \times 4/24) + (11 \times 13/24)$$

$$\Delta\mu_{winter} = 14.25 \text{ €/MWh}$$

The annual average effect is then obtained by weighting these seasonal effects according to the number of days in each period:

$$\Delta\mu_{average} = (153/365 \times 5.83) + (92/365 \times 9.50) + (120/365 \times 14.25)$$

$$\Delta\mu_{average} \approx +9.51 \text{ €/MWh}$$

This scenario therefore applies an adjustment of **+9.51 €/MWh** to the deterministic component μ .

3) Adjustment of the **spike component (J)**

Step 1: Assumptions and calibration choices

Table H13. Candidate calibrations and selected adjustments for spike probabilities and magnitude in Stress scenario

Component	Expected mechanism	Evidence / assumption	Candidate values	Selected	Applied calculation
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Positive spike probability	Scarcity events become much more frequent	Figure 10–56 highlights an increase in very high-price hours in stressed scenarios	$\times 1.50 / \times 1.75 / \times 2.00$	$\times 2.00$	$p^+ = p^+_{\text{base}} \times 2.00$
Positive spike magnitude	Stronger upward price spikes	Higher intensity of price spikes due to system constraints and scarcity	$\times 1.10 / \times 1.25 / \times 1.40$	$\times 1.25$	$M^+ = M^+_{\text{base}} \times 1.25$
Negative spike probability	Fewer oversupply situations	Stress conditions reduce the occurrence of low-price hours	$\times 0.70 / \times 0.80 / \times 0.90$	$\times 0.80$	$p^- = p^-_{\text{base}} \times 0.80$
Negative spike magnitude	Stable intensity of negative prices	Negative prices are not assumed to become structurally deeper under stress	$\times 0.90 / \times 1.00 / \times 1.10$	$\times 1.00$	$M^- = M^-_{\text{base}} \times 1.00$

Step 2: Detail of the main calculation

Starting from the central scenario:

- Positive spikes = +12,43 €/MWh
- Negative spikes = -3,84 €/MWh

Calculation :

Positive spikes :

$$12.43 \times 2.00 \times 1.25 = 31 \text{ €/MWh}$$

Negative spikes :

$$-3.84 \times 0.80 \times 1.00 = -3.07 \text{ €/MWh}$$

Net effect :

$$31 - 3.07 = +27.93 \text{ €/MWh}$$

The net effect of spikes increases very significantly relative to the central scenario.

Positive spikes become both much more frequent and more intense, reflecting the numerous supply stress situations. Conversely, negative spikes decrease in frequency due to the scarcity of oversupply situations.

4) Adjustment of volatility σ

Baseline $\sigma \times 1.45$ to reflect system constraints and uncertainty.

5) Final calibrated parameter set & Consistency check

Table H14. Final calibrated parameter set for the Stress scenario

Parameter	Adjustment
$\Delta\mu$	+9.51€/MWh
Net spike effect	+27.93€/MWh
Positive probability	$\times 2.00$
Positive magnitude	$\times 1.25$
Negative probability	$\times 0.80$

Negative magnitude	×1.00
Volatility	×1.45

Consistency check: reconstruction of the average price

By combining the deterministic component and the spikes:

$$P_{Stress} = 63.5 + 9.51 + 27.93 = 100.94 \text{ €/MWh}$$

$$P_{Stress} \approx \mathbf{101 \text{ €/MWh}}$$

The stress scenario therefore leads to an average price significantly higher than in the other scenarios. This order of magnitude is consistent with the sensitivities analysed by Elia (*Adequacy & Flexibility*), whose Figure 10-54 indicates that an exogenous cost shock (notably linked to gas prices) may generate a price difference of **25 to 35 €/MWh**.

Summary table

Table H15. Summary of calibrated parameter sets across scenarios

Parameter	Baseline	Current Commitments (CC)	Constrained Transition (CT)	Prosumer Power (PP)	Stress
μ (average deterministic level)	63.5	62.02	64.6	59.7	73.01
Positive probability	×1.00	×1.05	×1.30	×2.00	×2.00
Positive magnitude	×1.00	×1.00	×1.10	×1.25	×1.25
Negative probability	×1.00	×1.20	×0.80	×0.80	×0.80
Negative magnitude	×1.00	×1.05	×0.95	×1.00	×1.00
Volatility	×1.00	×1.10	×1.15	×1.45	×1.45
Net spike effect (€/MWh)	+8.59	+8.16	+14.9	+7.51	+28.0
Average scenario price (€/MWh)	72.14	70.7	79.5	67.2	101