Welfare Benefits of Co-Optimising Energy and Reserves

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Executive summary

The joint scheduling of energy and balancing capacity is an important step towards a future-proof electricity market design dominated by the large-scale integration of renewable energy sources, where ancillary services are to gain increasing importance. The current paradigm in Europe is a separation of the procurement of balancing capacity in day-ahead balancing markets from the trading of energy in the day-ahead energy market. This introduces inefficiencies, since energy and balancing capacity are interdependent due to fixed costs of starting up and operating generators, both energy and balancing capacity compete for finite generation capacity, and finite network capacity needs to be allocated for accommodating both energy trades as well as real-time balancing energy.

In this study we develop a two-stage model of the status quo of European day-ahead market clearing followed by balancing market operation which is compared to a co-optimisation benchmark. We further compare both setups to a regime of so-called market-based cross-zonal allocation of international network capacity, which adheres to Article 41 of the European Commission Electricity Balancing Guideline (European Commission, 2017).

We estimate that co-optimisation can deliver 678 million € per year of savings in operational costs relative to the status quo of sequential clearing of balancing capacity followed by energy. The market-based allocation of Article 41 of EBGL achieves 84 million € per year relative to the status quo. Extrapolating these figures to EU level based on energy production/consumption indicates a potential cost saving of 1281 million € per year from co-optimisation relative to the status quo and a potential cost saving of 159 million € per year from market-based relative to the status quo.

The drivers for these efficiency gains relate to the misrepresentation of fixed costs in sequential designs, which result in an inefficient commitment of resources with relatively low fixed costs. Due to their technical minima, these resources take up space from inflexible lower-cost resources that could have been used instead, in real time for serving forecast demand as well as imbalances. Co-optimisation avoids this pitfall by taking into account the fact that fixed costs are incurred once at the day-ahead stage for the provision of both energy and balancing capacity. It also allows a mix of commitments to be selected in real time that is not constrained by the rigidity of technical minima. This enables the system to rely as much as possible on low marginal cost resources.

The sequential clearing models rely heavily on intraday corrections. If such intraday corrections fail to materialise, we estimate an increase in the efficiency gains of co-optimisation, relative to status quo, of 1218 million € per year for the Core region, with the market-based allocation of Article 41 of EBGL capturing 239 million € per year of savings relative to the status quo for the same region.

Sequential designs rely on bidding opportunity costs for balancing capacity, and this can introduce errors in day-ahead scheduling in case of price forecast errors. This is especially so if one accounts for the appreciable price volatility that occurred in 2021 and 2022. Nevertheless, our modelling estimates that intraday corrections can largely absorb the adverse effect of these price forecast errors, to the extent that sequential designs with price forecast errors attain an average cost that is within the 95% confidence interval of the average cost of sequential designs without price forecast errors.

Bidding opportunity costs is not necessary in co-optimised multi-product energy and balancing capacity auctions (in the same way that bidding for the opportunity cost of cross-zonal capacity explicitly is not necessary in co-optimised multi-product energy and transmission auctions, e.g. SDAC). Doing so results in an explicit representation of opportunity costs of balancing capacity on top of its implicit consideration in the model, and thus scheduling inefficiencies. Our modelling estimates these inefficiencies at approximately 100 million € per year in the Core region, relative to the pure co-optimisation design.

1. Introduction

1.1 Context

Energy systems are rapidly evolving, and the deep integration of renewable resources such as wind and solar power are a dominant feature of this evolution. Due to their inherent unpredictability in supply, our limited ability to control these renewable resources, and their significant variability, the secure integration of these resources implies that ancillary services, and in particular balancing capacity (referred to equivalently as reserve throughout this report), are becoming an increasingly valuable service in electricity markets. This is happening while renewable resources are simultaneously exerting a downward pressure on energy prices due to their near-zero marginal cost. Electricity market design thus faces a call for evolution in order to be future-proof, in the sense of being able to reflect this substantial shift in the electricity market value chain.

Energy and balancing capacity are inherently interdependent. They are both provided by a common limited resource, namely power generation capacity. They both require a common fixed cost for their provision, namely a unit should be started up and running to be able to provide energy or balancing capacity, or both. And they both occupy limited capacity on the high-voltage network for their delivery. Ignoring this interdependency introduces economic inefficiencies, as well as misalignments in pricing.

Despite this interdependency, the status quo in European market operations clears balancing capacity separately from energy. Balancing capacity is typically cleared first before the day-ahead energy market and is followed by the day-ahead clearing of energy. Offers in the day-ahead energy market are commonly portfolio-based in most of the European Member States. Following the clearing of the day-ahead balancing capacity and energy markets, asset owners are required to nominate individual units that can deliver on the traded energy and balancing capacity. Resources that are cleared for balancing capacity effectively commit to submit offers into the balancing energy market, i.e. the real-time energy market, that are greater than or equal to the amount of balancing capacity that has been contracted in the day-ahead balancing capacity market.

The paradigm described above contrasts to a joint clearing of energy and balancing capacity, which is the norm in several international markets, including the US. We will refer to this paradigm of jointly clearing energy and balancing capacity in the day-ahead market as *co-optimisation*. The separation that takes place in Europe can be traced back to a number of institutional origins, related to governance, separation of system operation and market operation, a preference for portfolio bidding, and a number of other factors. Despite this established norm, European legislation carves out a path for using co-optimisation in Article 40 of the European Balancing Guideline (EBGL) (European Commission, 2017). The focus of

Article 40 is on allocating cross-zonal capacity in the day-ahead market for the exchange of balancing capacity, between Member States, also allowing to facilitate the exchange of balancing energy in real time. The cross-zonal trade of balancing energy is one of the most active frontiers in European market design over the past years. It follows the cross-zonal coupling of day-ahead markets, and the initiative is attested by the PICASSO, MARI and TERRE pan-European platforms which have been put in place for trading balancing energy from automatic frequency restoration reserves, manual frequency restoration reserves, and replacement reserves (aFRR, mFRR and RR) respectively. The allocation of cross-zonal capacity in day-ahead markets to facilitate this international trade of balancing energy is a consequence of article 40 of EBGL.

As an alternative to article 40, the EBGL also allows for an alternative approach, which is referred to as the so-called *market-based approach* for cross-zonal allocation of transmission capacity, described in article 41 of the EBGL. The idea in the market-based approach is to maintain the current paradigm of sequential clearing of day-ahead balancing capacity markets followed by day-ahead energy markets. A crucial difference between the market-based approach and the current paradigm is that day-ahead balancing capacity markets are intended to exchange balancing capacity or share reserves between bidding zones. For this to be possible, cross-zonal capacity needs to be allocated for that exchange at the day-ahead market stage. The market-based approach allocates this cross-zonal capacity by solving a balancing capacity market model which allows for cross-zonal exchange of balancing capacity but does not explicitly account for energy. Since the opportunity cost of procuring balancing capacity which could have been allocated to the energy market is a necessary input for this process, the market-based approach foresees alternative methods for estimating the incremental cost of withdrawing cross-zonal capacity from the day-ahead energy market[1], e.g. the energy price spread documented from previous energy market sessions. This cost of allocating cross-zonal capacity to the balancing capacity market is then used as input in the balancing capacity market model[2]. Once the day-ahead balancing capacity market is cleared, the amount of transmission capacity that is used for trading balancing capacity between zones is removed from the day-ahead market model, which is run in the final step of the market-based approach. The process is depicted graphically in Figure 1.

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[1] ENTSO-E, Explanatory document to the Energinet, Fingrid, Statnett and Svenska kraftnät proposal for the establishment of common and harmonised rules and processes for the exchange and procurement of balancing capacity and for the application of a market-based allocation process in accordance with Article 33(1) and Article 38(1) of the Commission Regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing, December 2019

[2] https://consultations.entsoe.eu/markets/nordic-tsos-proposals-for-the-methodology-for-a-ma/supporting_documents/Explanatory%20document%20to%20article%2038.pdf

Figure 1: A graphical depiction of the market-based approach for cross-zonal capacity allocation for the trading of balancing capacity between European Member States according to Article 41 of the EBGL.

Co-optimisation, as described in Article 40 of EBGL, is perceived as a complex and burdensome policy measure by many market participants. On the other hand, it is viewed as a welfare-enhancing solution by policy makers. The market-based approach of Article 41 is seen as a middle ground which aims at achieving some of the intended benefits of co-optimising without affecting the existing governance structure and design of the European markets as deeply as the co-optimisation alternative. In this work we contribute to the policy discourse by attempting to quantify the potential welfare gains of a move towards co-optimisation à la Article 40 relative to the status quo of separate balancing capacity and energy markets without cross-zonal exchanges of balancing capacity, and by estimating what fraction of these benefits can be reaped by the market-based approach of Article 41.

1.2 Related literature

The topic of co-optimisation relates to broader issues of market design, including the degree of centralisation in electricity markets and unit versus portfolio-based operations (Wilson, 2002), (Ahlqvist, Holmberg, & Tangerås, 2018). It is not our intention to cover these topics in detail here. Instead, we briefly describe the idea of co-optimisation which is juxtaposed to sequential clearing throughout the report. The idea of co-optimisation is to effectively conduct a multi-product auction that simultaneously clears energy and balancing capacity. The intention is to optimise both the allocation of these interdependent products, but also to price them consistently, since an agent that can offer both is looking at the profit margins generated by the different markets when deciding how to allocate its generation capacity. The principle of multi-product auctioning of energy and balancing capacity is no different than that of the multi-product auctioning of energy and transmission capacity: there too we have a joint allocation (of energy and network access), and the two are priced jointly, thereby giving rise to prices that differ between bidding zones. For reasons of legacy and institutional constraints, whereas European day-ahead markets co-optimise energy and transmission, they do not include balancing capacity in the existing day-ahead multi-product auction.

The value of co-optimising energy and balancing capacity was identified early on in US market design. Notably, the Midcontinent ISO received the prestigious Franz Edelman award in 2011 for demonstrating how a shift to branch and bound optimisation technology for co-optimising energy and reserve in the day-ahead market resulted in an estimated 2.1-3 billion US dollars over the period of 2007 to 2010.

The benefits of co-optimisation for the European market have also been articulated in early work by European researchers (Doorman & Van Der Veen, 2013). Models for quantifying the performance of European markets on realistic case studies that rely on sequential models of European market clearing have been developed in previous work by the authors of this work (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017), and are used as the modelling basis for representing the status quo of sequential market clearing in the present analysis.

The implementation of co-optimisation in the sense of Article 40 of the EBGL, and the challenges that emerge when considering the interplay between the cross-zonal trading of balancing capacity and network constraints, is considered in a study led by N-SIDE (N-SIDE; AFRY, 2020). This report was followed by a detailed exposition of the required amendments to the EUPHEMIA algorithm (N-SIDE, 2022) for enabling the introduction of balancing capacity in the pan-European algorithm that couples day-ahead energy markets. Institutional challenges related to the implementation of co-optimisation are carved out in an implementation impact assessment that was recently led by ENTSO-E (ENTSO-E, 2021).

The inefficiencies of sequential market clearing in European markets have been analysed in the academic literature in the past. The focus in past studies has often been on the treatment of network constraints, namely the classical zonal versus nodal debate (Kunz, 2013). Previous work on this topic has also been conducted by the authors of this work (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017), (Aravena, Lété, Papavasiliou, & Smeers, 2021), and the modelling framework that is developed in this work is also adopted in the present study. An important attribute of these studies is the quantification of how irrevocable scheduling decisions[3] that result from day-ahead markets can affect the efficiency of operating the system in real time. This has been the focus of the classical literature on stochastic unit commitment (Takriti, Birge, & Long, 1996). Following on this paradigm, we adopt a modelling convention that dates back from the work of Ruiz et al. (Ruiz, Philbrick, & Sauer, 2009), and is also adopted by the authors of the present work (Papavasiliou & Oren, Multi-Area Stochastic Unit Commitment for High Wind Penetration in

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[3] We consider two types of scheduling decisions in the energy market, following standard academic and industry terminology. Commitment throughout the report refers to the on-off status of units, and dispatch refers to the setpoint, or equivalently the amount of energy production/consumption of a given asset.

a Transmission Constrained Network, 2013), whereby units are differentiated between fast and slow, depending on whether or not they can adapt their on-off status in real time.

The modelling of multiple reserve products is another interesting aspect of our analysis. We focus on automatic and manual frequency restoration reserves in our work, in the spirit of previous analyses by the authors (Papavasiliou & Smeers, Remuneration of Flexibility using Operating Reserve Demand Curves: A Case Study of Belgium, 2017), with activation setpoints that vary every 4 seconds (in the case of aFRR) to 15 minutes (in the case of mFRR). The pan-European balancing energy platforms PICASSO and MARI have recently been put in place for the cross-border trade of balancing energy between different Member States.

The trade of balancing energy through MARI and PICASSO occurs across bidding zone borders. Since balancing capacity may or may not be activated in real time, this raises an interesting challenge of reserve deliverability. In the existing academic literature, the challenge of reserve deliverability has often been addressed by focusing on specific contingencies or assuming predefined distributions for imbalances (Zheng & Litvinov, 2008), (Chen, Gribik, & Gardner, 2014). Instead, in our analysis we present a novel model for reserve deliverability that relies on results from computational geometry (Bemporad, Filippi, & Torrisi, 2004), and ensures reserve deliverability in a flow-based network without any assumptions on the distribution of imbalances. This guarantee of reserve deliverability is referred to in the professional literature (N-SIDE; AFRY, 2020), (N-SIDE, 2022), (ENTSO-E, 2021) as the *deterministic requirement* for trading cross-zonal balancing capacity. Although the deterministic requirement results, in principle, in a computationally hard problem (Nohadani & Kartikey, 2018), we are able to tackle the deterministic requirement in the market clearing model through a linear programming approximation. Our approximation of the requirement is empirically observed to strike an acceptable balance between computational scalability and conservativeness.

1.3 Goal and structure of the study

Our analysis is supporting the ongoing policy debate between the European Union Agency for the Cooperation of Energy Regulators (ACER) and market stakeholders regarding the design of European day-ahead markets for the cross-zonal trade of balancing capacity. For reasons that are explained in section 1.1, this is a key market design discussion for the future of the European market, and our analysis serves to offer a quantitative backing and precise description of the pros and cons of alternative design choices.

The report is structured as follows: section 2 discusses the sources of inefficiency in the sequential clearing of balancing capacity markets followed by energy markets. Section 3 outlines the methodology that is employed in our study in further detail. The case study of the Core region of Europe is described in section 4, where we also present the results of our analysis. Section 5 summarizes the conclusions of our study. A number of appendices are included in this report, where we provide an explanation of notation and acronyms, a detailed account of our modelling assumptions, the data sources for our analysis, as well as additional simulations that have been performed in order to address targeted policy questions.

2 Sources of inefficiency

Breaking up inherently interdependent processes into pieces introduces inefficiencies. We focus the discussion in this section on inefficiencies related to market price forecast errors (section 2.1) and fixed costs (section 2.2), and we discuss the importance of intraday corrections in section 2.3.

2.1 Price forecast errors

Energy and balancing capacity interact, because they are both sourced from a given amount of generation capacity, and they are mutually exclusive. Co-optimisation resolves this challenge by accounting for this mutual exclusiveness in the auction model that clears the energy and balancing capacity market both at the same time. By contrast, sequential market clearing where balancing capacity is cleared before energy requires agents to anticipate the market price of energy, so that they can decide on the asking price for balancing capacity, which can be set equal to the profit margin that they forego from offering their capacity into the energy market. Concretely, the opportunity cost of a generator g with a marginal cost MC_g which anticipates an energy price λ^* can be expressed as:

$$\max\left(0, \lambda^* - MC_g\right) \quad (1).$$

A rational agent bids this opportunity cost into the balancing capacity market. It can be proven that, in a market with convex costs and constraints[4], if all agents correctly anticipate the perfectly competitive energy price, then the outcome of sequential market clearing is identical to that of co-optimisation. The intuition of this equivalence result is best understood in a single-period setting. The co-optimisation solution in such a setting can be achieved by allocating units with lower marginal costs for energy and more expensive units for balancing capacity. Note that this behaviour is precisely replicated by sequential market clearing,

[4] Convexity is violated whenever we require binary/on-off/take-it-or-leave-it decisions in order to represent costs and constraints. Examples of non-convexities include block orders, unit commitment decisions, min load costs, and startup costs.

because units with higher marginal costs effectively face lower opportunity costs in the balancing capacity market, as implied by equation (1). If all agents anticipate the same energy market prices, the agents with the highest marginal costs are therefore the ones to be cleared with highest priority in the balancing capacity market. The subsequent energy market is then cleared according to the merit order of the leftover units. Note that this is *precisely* the same outcome as that of co-optimisation.

Anticipating perfectly competitive energy prices becomes a tall ask for market participants, especially in the presence of multiple interacting balancing capacity products and with markets of higher time resolution. Errors in market price forecasts can distort the efficient allocation of balancing capacity under sequential clearing, which can in turn lead to suboptimal matching in the energy market. Market price forecast errors therefore become a focal point of our analysis. Our methodology for simulating market price forecast errors is described in section 3.3.

2.2 Fixed costs

Fixed costs are costs incurred by a power generation unit for producing a non-zero amount of output[5]. Fixed costs are a complicating factor because they are incurred for providing both energy but also spinning balancing capacity. However, once a unit is started up for one or the other reason, it can provide *both* energy and balancing capacity. This points to the fact that these fixed costs are fundamentally non-separable when it comes to delivering energy and balancing capacity.

Forcing a separation in the market clearing processes can lead to a situation where units with lower fixed costs and higher variable costs are inefficiently committed. This traces to the misrepresentation of fixed costs in the energy and balancing capacity auctions under sequential designs. The point is illustrated in appendix B. This effect, combined with the technical minimum of such units, can result in the inefficient displacement of low-cost technologies, as we demonstrate in section 4 of our report.

2.3 The role of intraday adjustments

It can be argued that some of the effects that are described above may be of minor importance, since agents can correct their schedules and commercial positions after day-ahead market clearing and before real time. Our analysis is mindful of this phenomenon, and therefore relies on a balancing market model that simulates real-time operations *after* the

[5] Technically, these are referred to in economics as short-term quasi-fixed costs. They include startup and minimum load costs.

day-ahead market clears, as we describe in section 3.2. The question ultimately becomes which decisions are truly irrevocable in the day-ahead time stage (e.g. unit commitment decisions or dispatch setpoints of certain technologies). Our modelling methodology, which is described in section 3, is tailored to precisely quantify the effect of these irrevocable decisions. Note, however, that major reshuffling between day-ahead commercial positions and real-time physical positions places a big burden on intraday adjustments and may, to a certain extent, be wishful thinking, which is why we analyse the sensitivity of our results to the degrees of freedom that can be adjusted in the intraday time stage in section 4.

3 Methodology

This section describes the methodology that we employ in our analysis. Section 3.1 describes the models that we use for representing day-ahead market operations, while section 3.2 describes the real-time balancing energy market model. Section 3.3 describes the process that we use for sampling price forecast errors, which are drivers for opportunity costs that are a crucial input in our analysis. Section 3.4 lays out some limitations in our analysis and discusses the extent to which such deviations are relevant for our assessment. Additional technical details on the methodology are provided in appendix D. Appendix E presents the mathematical formulation of the detailed market models that are used in our analysis.

3.1 Day-ahead market clearing

In this section we present the day-ahead market models that are developed for the status quo, the market-based allocation approach of Article 41 of EBGL, and the co-optimisation of Article 40 of EBGL.

All models have a 15-minute time resolution, are unit-based, represent upward and downward aFRR and mFRR, and employ unit commitment constraints that account for minimum up and down times, ramp rates, and planned outages. Although European market operations are typically portfolio-based, the unit-based assumption offers a coordination advantage to the sequential market models and is anyway the only approach possible given the data that is available. This assumption is discussed further in section 3.4. For all day-ahead models, we distinguish technologies between fast and slow. Fast and slow units can cover the needs of both aFRR and mFRR. Fast units are assumed to be able to cover mFRR even if they are offline.

3.1.1 Status quo

The status quo is represented by a day-ahead balancing capacity market model which is followed by a day-ahead energy market model. The balancing capacity market model aims at minimising the sum of fixed costs plus opportunity costs, with the latter being derived from equation (1). We assume that the base energy price that is used for the estimation of opportunity costs in the sequential clearing model is based on the energy price of the co-optimisation model. We add to this base energy price a price forecast error, which aims at accounting for the fact that generators cannot perfectly anticipate the energy price that would efficiently coordinate the market, as we discuss in section 2.1. The fixed costs that are included in the objective function of the model include both the minimum load cost of running a unit at its technical minimum plus any additional power generation implied by downward mFRR and aFRR capacity, as well as startup costs. Again, in the spirit of implementing a best-case (if not overly optimistic) version of the sequential clearing model, we assume that aFRR and mFRR are cleared jointly in a single balancing capacity market model that accounts for the interdependencies of the two balancing capacity products. We therefore ignore potential coordination inefficiencies and pricing distortions that result from the fact that sequential clearing of balancing capacity does not account for the one-way substitutability of balancing capacity products (Oren, 2001), and this despite the fact that at least certain European markets (e.g. the Nordics) aim at advancing with a sequential clearing of balancing capacity products (aFRR first, followed by mFRR). Min up/down times, and ramp rates are accounted for in this balancing capacity market model, even though these are not accounted for at unit level in a portfolio-based design. Fixed reserve requirements are used. The sources for these reserve requirements are discussed in section 4.1. The balancing capacity prices are computed from the dual multipliers of the market clearing constraints after binary variables are fixed to their optimal values (O'Neill, Sotkiewicz, Hobbs, Rothkopf, & Stewart, 2005). The status quo model does *not* trade balancing capacity between areas, with the exception of 80 MW that are traded between Austria and Germany, which aim at representing the Austrian-German aFRR cooperation[6] initiative.

Once the balancing capacity market model is cleared, we proceed to solve the day-ahead energy market model. This model is also unit-based and amounts to a unit commitment model where the aFRR and mFRR allocations of the balancing capacity market model are fixed. Since the unit commitment model directly models the interaction between unit commitment decisions and the ability of a unit to offer aFRR and mFRR, the model proceeds to start up and run units so that they can honour their aFRR and mFRR allocations, as decided in the balancing capacity model of the previous step. A zonal transmission network model with flow-based constraints is employed. The full capacity of cross-zonal network elements is made available to the energy market, and this is an essential distinction between the status

[6] https://www.entsoe.eu/network_codes/eb/alpaca/

quo model and the market-based allocation of section 3.1.2. Technical minimum and maximum constraints are included in the model, as well as ramp rates and minimum up and down time constraints. The objective function of the day-ahead energy market model aims at minimising load shedding costs plus generating unit fuel costs, startup costs, and minimum load costs.

We note that the following assumptions could be argued to bias our analysis in favour of the sequential design:

- We introduce fixed cost, ramp rates, and min up/down times in the first step of the sequential clearing model in a way that actually exceeds the expressiveness of the existing bidding language of the European market. Concretely, our model of balancing capacity markets is a unit-based model where the interdependency between starting up a unit and delivering balancing capacity is represented through precise unit commitment constraints that also account for ramp rates and the minimum up and down times of units and the interactions across balancing capacity products as well as between energy and balancing capacity. This is a modelling choice that offers a best-case (if not overly optimistic) outlook on the ability of the bidding language within a portfolio-based design to allow for endogenizing these constraints and costs. Portfolio owners in certain markets can trade their positions or disaggregate market outcomes into nominations of individual physical units, which can rationalise this optimistic modelling of the balancing capacity market to a certain extent.
- We use the energy price of the co-optimisation model as input for the computation of opportunity cost for the balancing capacity market of the sequential design, which is an optimistic outlook on the ability of agents to anticipate efficient opportunity costs.

3.1.2 Market-based allocation

The model for representing market-based allocation is almost identical to that of the status quo (section 3.1.1), with the important difference that bidding zones are allowed to trade balancing capacity for aFRR and mFRR in the market-based allocation approach.

The representation of the trading of balancing capacity introduces a notable complexity to the model, that was first highlighted in (N-SIDE; AFRY, 2020). A TSO that procures a certain amount of balancing capacity is effectively procuring an option to activate any amount of balancing energy in real time from zero up to the amount of balancing capacity that it has procured. In meshed networks governed by flow-based constraints, the market clearing model needs to be mindful of allocating these options in a way such that, no matter the pattern of activation of balancing energy in different bidding zones, the resulting flows do not violate the constraints of the network. This is a requirement that has been dubbed by

ENTSO-E as the so-called *deterministic requirement* for cross-zonal balancing capacity trade. This is a far more demanding requirement than scheduling energy trades that are planned to take place with certainty. The underlying model can be represented as a robust optimisation problem with decision-dependent uncertainty (Nohadani & Kartikey, 2018), which is inherently intractable. This challenge is resolved by (N-SIDE, 2022), where a formulation is proposed that aims at approximating the deterministic requirement through an inscribed box (Bemporad, Filippi, & Torrisi, 2004) that lies within the polytope of feasible cross-zonal balancing capacity trades. Whereas the latter is intractable to characterize, the former can be described straightforwardly by only ensuring that the upper-right corner of this box is within the polytope of feasible cross-zonal balancing capacity trades, and this turns out to be a mathematically tractable formulation.

In addition to allowing for the trading of balancing capacity, we also introduce a constraint that requires no more than 10% of the remaining available margin of each critical network element with contingency to be allocated for the trade of balancing capacity. This constraint corresponds to an actual operational limit that is imposed by European regulation[7]. The rationale of the constraint is to prevent excessive allocation of cross-zonal capacity to the trade of balancing capacity. The effect of this constraint on the efficiency of the market-based method is analysed in our study. Moreover, we require that a bidding zone cannot import more than 50% of its balancing capacity requirement from other bidding zones (see footnote 7).

3.1.3 Co-optimisation

The co-optimisation model jointly optimises the allocation of energy and balancing capacity in a single multi-product day-ahead auction. Upward and downward aFRR and mFRR are thus traded jointly with energy in this model. In contrast to sections 3.1.1 and 3.1.2 models, this one accounts directly for the fact that energy and balancing capacity are mutually exclusive when representing the technical minimum and maximum constraints. As in the case of the previous models, min up/down times and ramp rates are represented in the model. The cross-zonal trade of balancing capacity is possible in this model, as in the market-based approach, and the deterministic requirement on the trade of balancing capacity is enforced. The network is represented again through flow-based constraints. Following

[7] Article 41(2) of (European Commission, 2017) states that: "*Cross-zonal capacity allocated on a market-based process shall be limited to 10 % of the available capacity for the exchange of energy of the previous relevant calendar year between the respective bidding zones or, in case of new interconnectors, 10 % of the total installed technical capacity of those new interconnectors.*".

European regulation[8], we impose a requirement that a bidding zone cannot import more than 50% of its balancing capacity requirement from other bidding zones. We observe that the constraint is not binding in the results. Note that this constraint is also present in the market-based model, where it is also non-binding.

The objective of this model is to satisfy energy demand and balancing capacity requirements at least cost. Cost is measured as the sum of involuntary load shedding plus fixed min load and startup costs of units plus variable fuel costs. Note that the co-optimisation model does not require price forecast errors as input, since the opportunity cost of allocating generation capacity for reserve is accounted for, and optimised, endogenously in the model.

3.2 Balancing market clearing

An important aspect of our methodology is that we aim to quantify how distortions in day-ahead market clearing affect the physical operation of the system in real time, which is the ultimate source of inefficiency in our analysis. For this purpose, it is necessary to capture the interplay between irrevocable decisions that are reached in the day-ahead stage, and how they limit the operation of the market in real time. These irrevocable decisions include unit commitment and the setpoint of certain technologies. The real-time market clearing model that emerges from fixing these decisions essentially represents the real-time balancing market, and it is the model that is used for ultimately measuring the efficiency of how the system is operated. The real-time model is common to all three approaches, and the only differentiating factor between the market designs is how these designs affect the irrevocable decisions (unit commitment and setpoint of certain technologies) by which we enter real-time operations. The real-time model has the same 15-minute time resolution as the day-ahead models.

To capture the effect of irrevocable unit commitment decisions on real-time operations, we assume that whichever units are committed for balancing capacity in the day-ahead time stage still continue to be committed in real time. Moreover, we fix the setpoint of nuclear units to their day-ahead schedule.

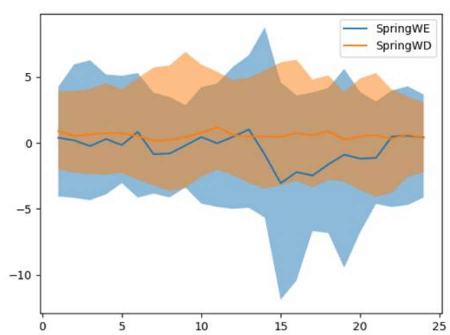
The balancing energy market model is otherwise similar to the day-ahead models presented above. It is an energy-only model, and costs include the variable costs of all technologies, as well as the fixed startup and min load costs of fast units. The network is represented again through flow-based constraints, where we repeat the same flow-based constraints of the day-

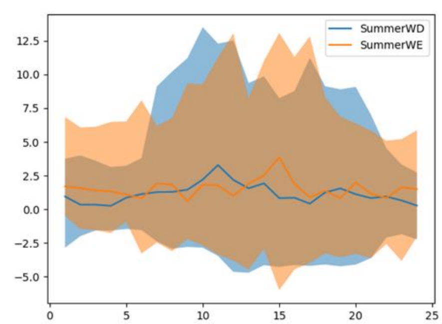
[8] Annex VII of the System Operation Guideline (SOGL), (European Commission, 2017) states that: "*The TSOs of a LFC block shall ensure that at least 50 % of their total combined reserve capacity on FRR resulting from the FRR dimensioning rules in Article 157(1) and before any reduction due to the sharing of FRR in accordance with Article 157(2) remains located within their LFC block.*".

ahead model in the real-time model. Samples of balancing energy market operations are simulated by drawing a random realisation of renewable forecast errors, which the system is called to balance in real time.

3.3 Price forecast errors

As we discuss in section 2.1, price forecast errors affect the opportunity cost by which agents value the balancing capacity that they offer in the sequential market clearing designs (status quo and market-based allocation). In order to estimate these forecast errors based on historically available data, we compute the difference in prices between a given day and the preceding day of the same day type for the entire range of our dataset[9]. To this data we add independent Gaussian errors, in order to represent the fact that price forecast errors may differ between different market participants. This Gaussian noise has a mean of zero and a standard deviation which is 3% of the average day-ahead price. Figure 2 presents the 25th and 75th percentile of price forecast errors for the Belgian bidding zone, as estimated from the aforementioned procedure.





[9] We only use 2020 for historical price data. We originally also included 2021 and 2022 in our analysis, however this introduced significant price forecast errors due to the price spikes that resulted from the European natural gas crisis. We refer the reader to section 4.2 for a sensitivity analysis regarding this assumption.

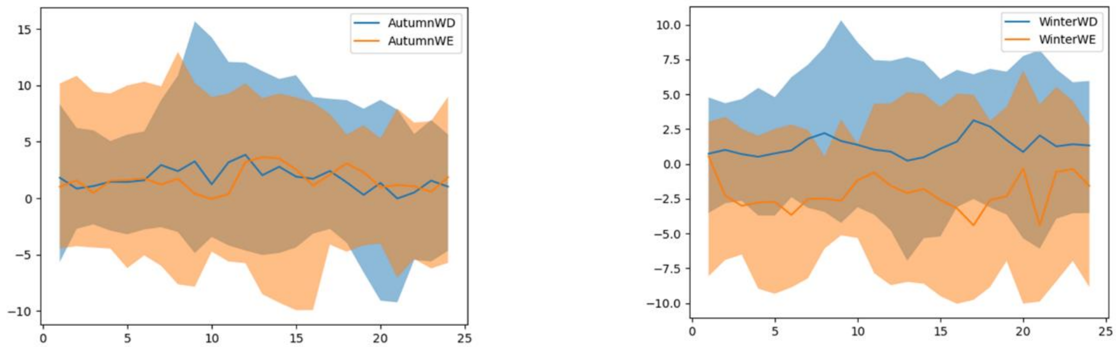


Figure 2: Price forecast errors for the Belgian bidding zone for the eight different day types. The shaded areas represent the 25th and 75th percentile for each hour of the day.

3.4 Caveats

In this section we discuss the effect of certain modelling assumptions on our analysis. We model the European market using a unit commitment model following the methodology in (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017), as opposed to attempting to represent the bidding products that are used in the European day-ahead electricity market. This is a methodological necessity, because there is no historical record of bids in the energy and balancing capacity markets in a co-optimised setting, therefore we would need to devise/invent bids if we would insist on representing European market bids, as opposed to actual physical assets. We comment on how this may bias the analysis in favor of the status quo in the end of section 3.1.1.

In particular, we do not emulate the current products of the European market (simple bids, block bids, complex orders, PUNs, etc.), since we consider them as portfolio-based proxies that anyway attempt to capture the true economical and technical characteristics of aggregations of individual thermal units. The assumption of a unit-based unit commitment and economic dispatch model also implies that we do not foresee an encoding of unique aspects of the European day-ahead market, particularly the no-PAB (no paradoxically accepted bids) requirement, in our market clearing model. Instead, and in order to cope with the pricing of non-convexities, our mathematical models are tailored to support so-called integer programming pricing as proposed by (O'Neill, Sotkiewicz, Hobbs, Rothkopf, & Stewart, 2005) (which can be interpreted as "marginal pricing" *after* binary variables are fixed to their optimal values).

Notwithstanding our assumption, the operation of individual physical assets can be approximated to a certain extent with EUPHEMIA product specifications. As a naive approximation, for instance, one might consider mutually exclusive blocks which enumerate a set of alternative commitment trajectories. This same naive approximation may apply to portfolios, where one could again consider trajectories of combinations of individual assets, and assign a fixed and variable cost to each of these trajectories. Arguably, mutually exclusive block offers (with minimum acceptance ratios less than one) can, to a certain extent, approximate the combinations of trajectories that a unit commitment model can consider, and then these offers can be linked (in the sense of multilateral bid linking (N-SIDE, 2022), (ENTSO-E, 2021)) with balancing capacity offers (without an associated price, i.e. a zero opportunity cost).

The fact that we use a unit-based model should not be confused with ignoring portfolio effects. Concretely, our analysis accounts for the possibility of portfolio owners to fully coordinate the use of their assets in the intraday time stage. We refer the reader to the discussion in section 2.3, as well as the simulation results of section 4.2, for additional discussion on the effect of the coordination efficiencies of portfolios.

Another assumption that is important to highlight is that we assume that co-optimisation in the sense of Article 40 of EBGL is properly implemented as an integrated single-shot optimisation of energy and balancing capacity. Although this might require a tighter coordination between power exchanges and TSOs in practice, which may be deemed as an institutional barrier in the European market design context, we nevertheless insist on performing our calculations without artificially splitting the process into a multi-step procedure, since this would, to a certain extent, defeat the purpose of co-optimisation.

One additional difference between our model and actual market operations is the representation of the balancing capacity market in the sequential clearing models (the status quo model which corresponds to the existing market design, as well as the market-based model that is foreseen in Article 41 of EBGL). Here, we opt for an optimistic over-estimation of the potential performance of the European day-ahead balancing capacity market, whereby aFRR and mFRR are cleared jointly, where we assume that units can be bid into the market individually, and where we further assume that their fixed costs can be separated from their opportunity costs. This assumption anyway biases our analysis in favour of sequential market clearing designs.

One additional point that may be interesting to investigate is the effect of our assumptions on how prices are formed in a non-convex setting. Concretely, we adopt the approach of (O'Neill, Sotkiewicz, Hobbs, Rothkopf, & Stewart, 2005) for computing prices in our non-convex models, but alternatives could also be considered, e.g. the linear programming relaxation of the market model (which is a closer approximation of convex hull prices). This distinction matters, because it affects to what extent market prices can capture fixed costs in the price signal. And this in turn can affect the economic efficiency of different market design variants in our study because the energy prices computed by our co-optimisation model feed into our estimate of opportunity costs in the sequential market clearing models. The effect of this assumption on our results may therefore warrant a sensitivity analysis in future work.

Finally, we assume perfect competition and truthful bidding in our analysis. Thus, problems with market concentration in existing balancing capacity markets are not accounted for in our analysis. The social welfare impacts of improved competition due to co-optimisation are thus not quantified in our analysis. The possibilities for the sharing of reserves[10] that are unlocked by co-optimisation and the market-based design are also not captured by our analysis.

4 Case study

In this section we describe the results of our analysis on a case study of the CORE region. Section 4.1 presents our sources and assumptions for input data. Section 4.2 compares the welfare performance of the different designs as well as various sensitivities. Additional details about the case study are provided in appendix F.

4.1 Input data

We analyse the Core region, which includes the following countries: Austria, Belgium, Croatia, Czechia, France, Germany, Hungary, Luxembourg, the Netherlands, Poland, Romania, Slovakia, and Slovenia.

The database that concerns Central Western Europe (CWE) has been developed by our team since 2014 from a variety of sources that are described in a number of scientific publications, including (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017). This includes detailed technical and economic information about networks, generators, loads, and renewable supply, that has been assembled from a variety of public and private databases. The details of how we have assembled the generation mix for the European market are described in (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017).

Load, renewable supply and hydrology. Demand data is sourced from historical profiles of national consumption which are available in TSO websites and the ENTSO-E transparency

[10] *Exchange* of balancing capacity refers to the practice whereby a system operator can procure its own balancing capacity needs from a neighboring control area through exclusive access to the balancing capacity in question. In the *sharing* of balancing capacity, TSOs operating neighboring control areas gain non-exclusive access to the same balancing capacity, counting on the fact that the two system operators will not require the same resource simultaneously.

platform[11]. This includes data with both 15-minute as well as hourly resolution. Photovoltaic and wind supply data is sourced from TSO websites with a temporal resolution of 15 minutes. Hydropower injections are also sourced from TSO websites. Note that we do not model the medium-term planning of hydropower endogenously in our model, but rather consider the use of hydro as an exogenous parameter. On the other hand, we do model the short-term optimisation of pumped hydro resources and we also model hydro reservoirs by fixing their water level at the beginning and end of the day to their historical values. A detailed description of the model of pumped hydro resources, and their precise treatment in the co-optimisation and sequential designs, is provided in appendix E.

An operational year is described by considering eight representative days, which we refer to as day types. Day types affect the following input data: load, renewable supply, and hydrology. There are eight day types, one for each season and weekday versus weekend. The representative day of each day type is chosen using the approach described in (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017). For *each* day type we have 145 profiles of renewable supply data available. These samples are the input that is used in the real-time balancing market simulations. On the other hand, the day-ahead simulations are run using the average renewable supply data.

Network. As we discuss in section 3, we use a zonal flow-based model for representing the network in our study. The flow-based polytopes that are used in our analysis correspond to actual operations and are sourced from the JAO website[12]. We assign a flow-based polytope to each day by randomly selecting a day that belongs to the day type in question and selecting the corresponding polytope.

Generation. Generation data has been assembled from a database that has been provided to our group from industrial partners of our team. The system has an installed capacity of 594.347 GW, and the different technologies that are included in the mix are presented in Table 1. Fast units are those units that have a minimum down time that is no greater than four hours, regardless of technology. The model consists of 306 fast units with a total capacity of 139.634 GW, and 312 slow units with a total capacity of 182.961 GW. Wind and solar generation do not belong to either category.

Technology	**Capacity (GW)**
Biomass	12.034
Gas	87.728
Fossil hard coal	46.511
Waste	1.574

[11] https://transparency.entsoe.eu/
[12] https://publicationtool.jao.eu/core/finalComputation

Nuclear	82.087
Brown coal/lignite	38.281
Oil	6.685
Coal-derived gas	2.331
Hydraulic pumped storage	22.960
Wind	119.084
Hydraulic run of river	27.246
Hydraulic reservoir	19.273
Solar	128.553
Total	594.347

Table 1: Technologies and their corresponding capacity.

Reserve requirements. Reserve requirements are drawn from diverse sources and include requirements for aFRR and mFRR in both the upward and downward directions. Note that frequency containment reserve (FCR) is not represented in our model. For Poland, Croatia, Hungary, and Romania we obtain the reserve requirements from the ENTSO-E transparency platform. For Austria, France, Slovenia, Czechia, and Slovakia we have collected this information from direct communication with TSOs or national regulators. For Belgium, Germany, Luxembourg, and the Netherlands we use the websites of the national TSOs.

4.2 Welfare comparison

In this section we report on the costs of the alternative designs. This is equivalent to reporting on welfare when there is no load shedding (which is the case in all our models), since losses in consumer welfare are zero under all designs and the only driver of welfare is production cost. The results in this section focus on the comparison of the sequential designs to co-optimisation. Additional sensitivity analyses are presented in appendix G.

Cost comparison of alternative designs. The relative performance of the different market designs in terms of cost is presented in Figure 3. We note that co-optimisation improves costs of system operation by approximately 2.1% relative to the status quo, while the market-based design reaps 0.3% of these cost savings. The efficiency gains of the co-optimisation design translate to 678 million € per year for the Core region, while those of the market-based approach translate to 84 million € per year for the Core region, relative to the status-quo design. Extrapolating these savings to the produced and consumed energy of the entire EU for 2023 indicates a potential cost saving of 1281 million € per year from co-optimisation relative to the status quo and a potential cost saving of 159 million € per year from market-based relative to the status quo.

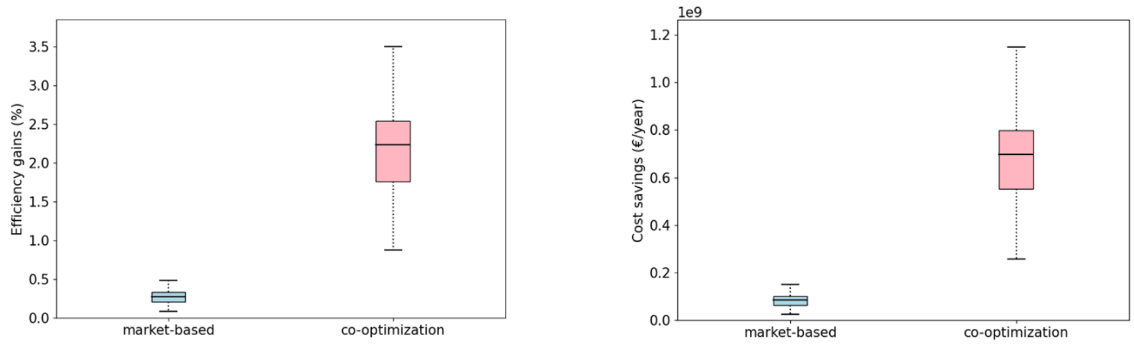


Figure 3: Cost comparison of the co-optimisation and market-based approach relative to status-quo. Relative values are presented in the left, and absolute values (in € per year) are presented in the right.

The inefficiencies of sequential market clearing, which already alluded to in section 2 and appendix B, can be attributed to the suboptimal commitment of units with high fixed costs for reserve, which leads to an inefficient dispatch of nuclear power in the energy clearing module. We now proceed to a detailed analysis of these efficiency losses in our case study.

The role of fixed costs. An important practical challenge in sequential designs is the fact that fixed costs are not decomposable. This means that fixed costs need to be committed once for delivering both energy and balancing capacity, and there is no natural way to decompose this fixed cost between providing one or the other. This presents market participants with the challenge of deciding how to offer fixed costs in the energy and balancing capacity market. As we explain in our modelling assumptions in section 3.1, we assume full fixed cost bidding in both the energy and balancing capacity market. Concretely, (i) fixed costs are assumed to be fully bid into balancing capacity markets, and (ii) for units that are not cleared in the balancing capacity market, their fixed costs are bid again in the day-ahead energy market that follows the balancing capacity market.

Figure 4 presents the balancing capacity allocations of co-optimisation and the sequential clearing design. The units are ordered on the x axis in order of increasing fixed cost (i.e. units to the right of the figure have a higher fixed cost). Orange crosses indicate units that are allocated to balancing capacity by each design, and green crosses indicate units that are committed by one design and not the other.

We observe that, whereas co-optimisation allows an allocation of balancing capacity for units with relatively high fixed costs (observe the green crosses further to the right of the left panel in the figure), the sequential clearing design avoids this. The co-optimisation design correctly commits these units because it does not misrepresent fixed costs, since fixed costs can cover two needs: energy and balancing capacity. On the other hand, sequential clearing misrepresents fixed costs, and chooses to avoid committing the units that are indicated with the green crosses in the left panel of Figure 4.

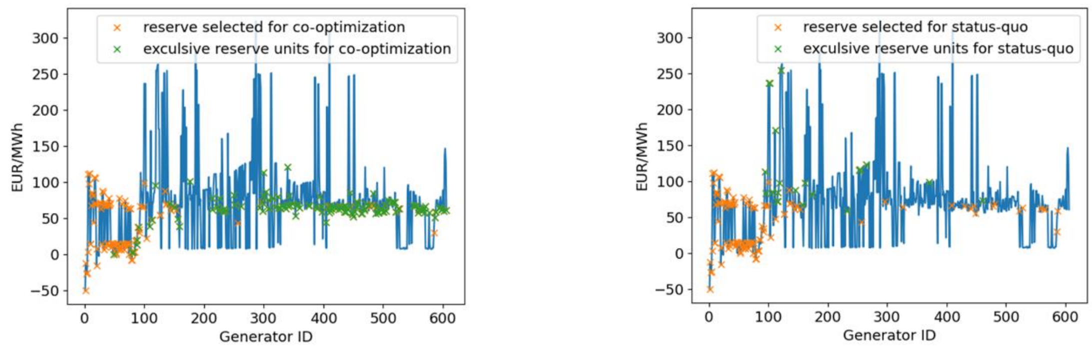


Figure 4: Balancing capacity commitment for co-optimisation (left) and status-quo (right). The y-axis is the marginal cost of the unit, while the x-axis is the generator index. The x-axis is ordered in order of increasing fixed cost.

The role of technical minima. An important driver for the efficiency gains of co-optimisation is the coordination between technologies with low marginal cost (such as nuclear technology) and the technical minima of thermal units. We now proceed to explain this phenomenon.

The left part of Figure 5 demonstrates that the co-optimisation design is able to use more nuclear energy. As indicated in Table 2, nuclear units are non-dispatchable, meaning that their real-time dispatch is fixed to the day-ahead setpoint and cannot be adapted to real-time conditions. The reason why the co-optimisation design is able to absorb more nuclear power in the day-ahead stage is that its production is not displaced by units that are running at their technical minimum. Instead, and as indicated in the right part of Figure 5, the sequential designs commit resources in the day-ahead stage that result in a higher sum of technical minima.

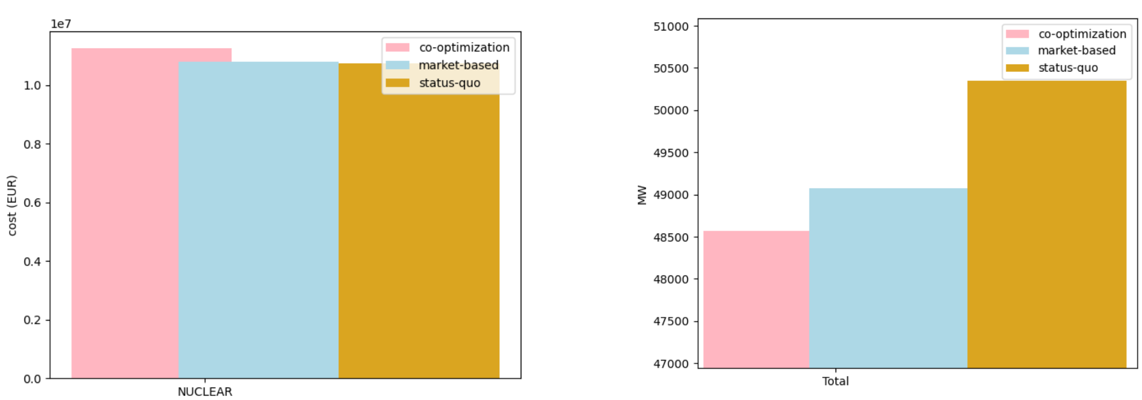


Figure 5: Left panel: dispatch of nuclear in the three designs in the day-ahead market. Right panel: sum of technical minimum of all units that are committed in the day-ahead stage under the different designs.

In order to understand why this is happening, we can categorize the units that are committed by the sequential designs in the day-ahead stage (after clearing both day-ahead balancing capacity and day-ahead energy) as follows:

- Natural gas units booked for balancing capacity. As indicated in Table 2, these units have a relatively high marginal cost and medium fixed costs.
- A certain number of units (which include coal, lignite, and natural gas) with high fixed costs but lower marginal cost compared to the gas units of the first category.
- Certain nuclear power units with high fixed cost but low marginal cost.

The co-optimisation does not commit the first category of units in the day-ahead stage. Instead, it uses the second category of units for covering balancing capacity requirements. This in turn implies that the first category of units is not taking up space from the dispatch of low-marginal-cost resources (such as nuclear energy).

The sequential design commits the first category of units because they are more attractive from the point of view of the balancing capacity auction due to their moderate fixed costs. However, it also commits the second category of units at the day-ahead energy market. Consequently, these units inefficiently displace nuclear units in the day-ahead energy auction. Instead, the co-optimisation design accounts for the fact that the fixed costs of the second category of units may be high, but these fixed costs can be incurred once for covering two purposes, i.e. satisfying both energy demand as well as balancing capacity requirements. Crucially, the accumulated technical minimum of the units that are committed in the day-ahead stage by the co-optimisation design is lower, and this allows for more nuclear energy to be dispatched in the day-ahead stage.

The role of intraday adjustments. The sequential clearing designs can benefit strongly from a drastic reallocation of units between the day ahead and real time. Concretely, units that are cleared for offering balancing capacity in the day-ahead time stage end up with a significantly higher energy setpoint in real-time operations. Certain Member States allow for bilateral out-of-market arrangements after the day-ahead market clears (e.g. trading balancing capacity responsibilities). It is not clear that intraday auctions or continuous intraday trading can serve this purpose, especially since the market products defined in these auctions are not necessarily offering a more expressive bidding language than the day-ahead market. It means that if the day-ahead market is subject to such coordination inefficiencies then the intraday market may be subject to similar coordination inefficiencies. Another alternative to bilateral out-of-market trades and intraday markets could be reallocations within portfolios. The perfect reallocation modelled in our analysis would implicitly require a single portfolio in the entire market, which is clearly an idealized assumption that is not (and cannot be, due to competition requirements) fulfilled in practice.

To establish this point, in addition to the welfare gains that are quantified by the full sequence of day-ahead and balancing market clearing, we also report on the welfare gains of co-optimisation in the day-ahead market alone.

Concretely, the co-optimisation model achieves efficiency gains of 3.9% relative to status-quo, which means that intraday and real-time adjustments are able to improve the wedge between co-optimisation and status quo from 3.9% to 2.1%. Similarly, the day-ahead market-based design achieves a performance improvement of 0.8% relative to status quo. This means that intraday adjustments decrease the wedge of market-based relative to status quo from 0.8% to 0.3%. The savings of the co-optimisation design relative to status quo, as documented by the day-ahead market model alone, translate to 1218 million € per year and the savings of the market-based design as documented by the day-ahead model alone translate to 239 million € per year for the Core region. Figure 6 depicts this point graphically, where we present the welfare gains of the market-based approach and of co-optimisation for the day-ahead models alone (which can be considered as an upper bound on efficiency losses, with no intraday adjustments) as well as the welfare gains from the real-time models (which can be considered as a lower bound on efficiency losses, with full intraday adjustments).

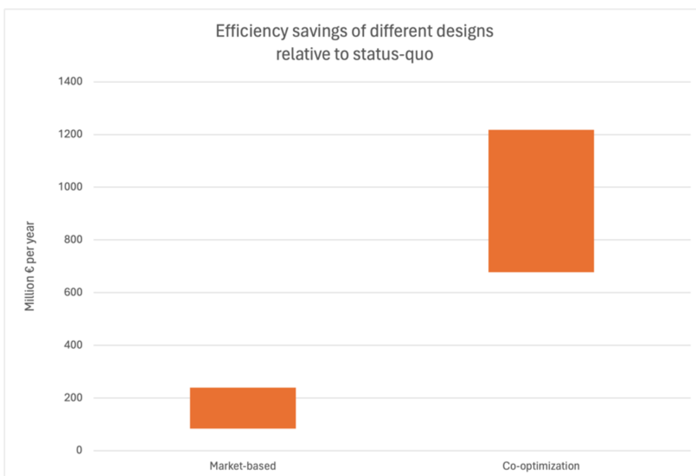


Figure 6: Efficiency savings of different designs relative to status quo. The upper bound corresponds to the results of the day-ahead market models alone, whereas the lower bound corresponds to the outcome of the balancing market, i.e. it accounts for intraday corrections.

Effect of price forecast error. Price forecast errors can introduce inefficiencies in the commitment of resources under the sequential designs, as we discuss in section 2.1. It turns out that, for our case study, these day-ahead inefficiencies can largely be corrected through intraday adjustments (assuming such adjustments are possible in practice). We now proceed to discuss this issue in detail.

Figure 7 presents the daily cost of operations under the two sequential designs, namely market-based and status quo. The left panel presents the performance when price forecast errors are calibrated against the historical price data of 2020 according to the procedure that is described in section 3.3 and appendix D3. The right panel performs the same exercise when price forecast errors are calibrated against the historical price data of 2020-2022, which includes two years of energy crisis in Europe, and thus arguably leads to greater price forecast errors. The runs with price forecast errors include the sampling of these errors, thus these are not point observations, but rather independent samples of costs, and the orange bar indicates the 95% confidence interval of the average cost. As we can expect, the increased price forecast errors in 2020-2022 which imply greater price forecast errors also imply greater inefficiency in the day-ahead market models, which is confirmed by the clearer separation between the orange bar and the blue dot in the right panel of Figure 7.

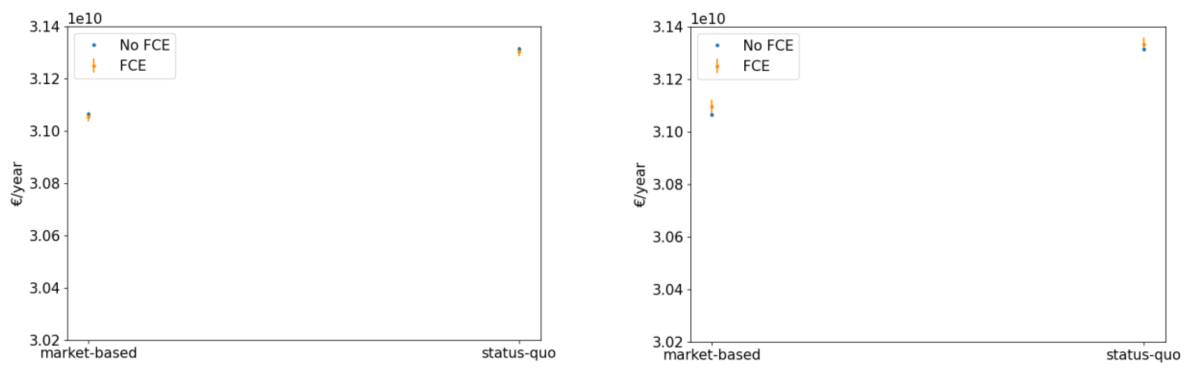


Figure 7: Daily cost of operation in day-ahead market clearing with and without price forecast errors. Left: price forecast errors based on 2020 historical price data. Right: price forecast errors based on 2020-2022 historical price data.

Whereas the day-ahead costs are more clearly separated in Figure 7, we note from Figure 8 that the costs without price forecast errors (blue dots) land within the confidence intervals of the models with price forecast errors (orange bars). Note also that what changes from the day-ahead to real-time simulations is the width of the orange bars, i.e. the variance of the observations in the real-time model, due to uncertainty in real-time imbalances. This observation means that cost differences between the models with and without price forecast errors are now within the range of statistical noise, and it cannot be ruled out that the inefficient commitments that are caused in the day-ahead due to price forecast errors are largely undone by intraday adjustments.

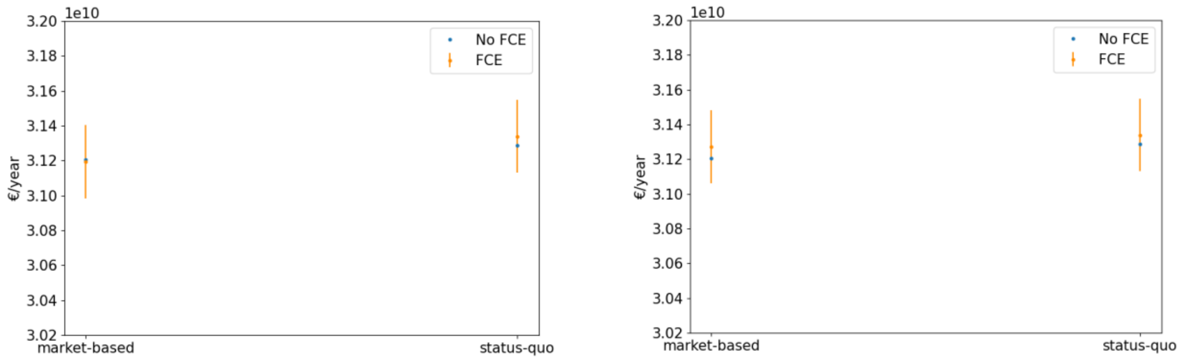


Figure 8: Daily cost of operation in real-time market clearing with and without price forecast errors. Left: price forecast errors based on 2020 historical price data. Right: price forecast errors based on 2020-2022 historical price data.

Figure 9 further supports the claim that intraday corrections can largely correct for inefficient day-ahead commitments. This figure indicates the amount of reserve capacity that is allocated to different units in the models with (orange, where we present average values) and without (blue) price forecast errors. The important observation in this figure is that, although the two models may commit reserves differently between the different units (due to price forecast errors), the same units are chosen for the provision of this reserve. Since commitment is the only irrevocable decision that concerns the operation of these units when moving from day-ahead to real-time operations, it means that the outcome of the models will be largely the same in real time, as both the model with and without price forecast errors will be facing largely the same set of irrevocable day-ahead decisions during real-time operation.

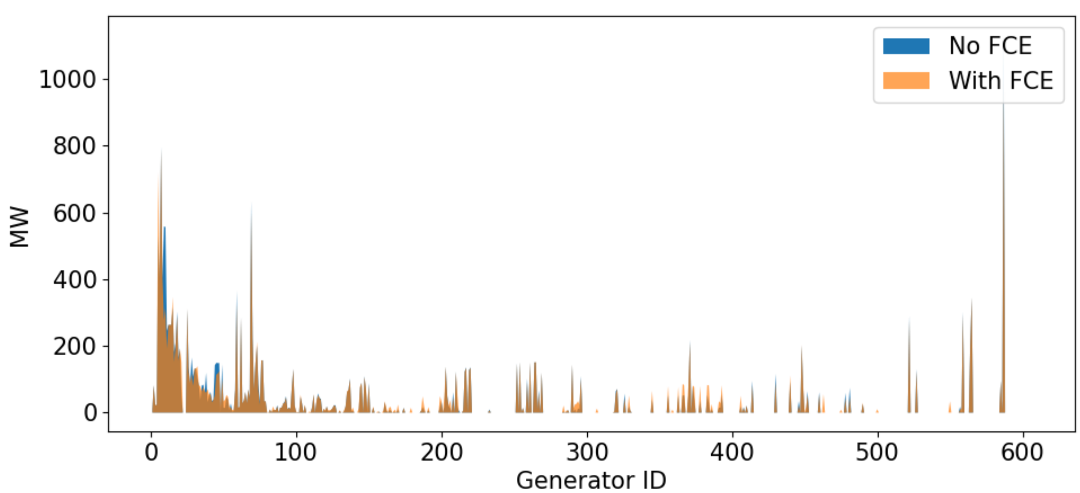


Figure 9: Amount of reserve committed in the models with and without price forecast errors in the status quo design.

Use of cross-zonal capacity. In Figure 10 we report the use of cross-zonal capacity on the different links of the CWE network (we do not present all links of the model, since there are too many and this would obscure the presentation of the results). The net position of the different bidding zones in upward balancing capacity (aFRR and mFRR), downward balancing capacity (aFRR and mFRR) and energy is presented in Figure 11.

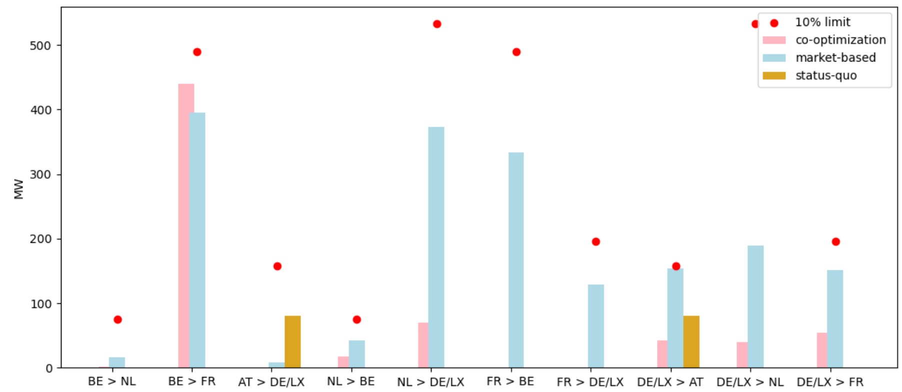


Figure 10: Use of cross-zonal capacity on the CWE links for trading balancing capacity (sum of aFRR and mFRR) under the different designs. The red dots indicate the 10% limit.

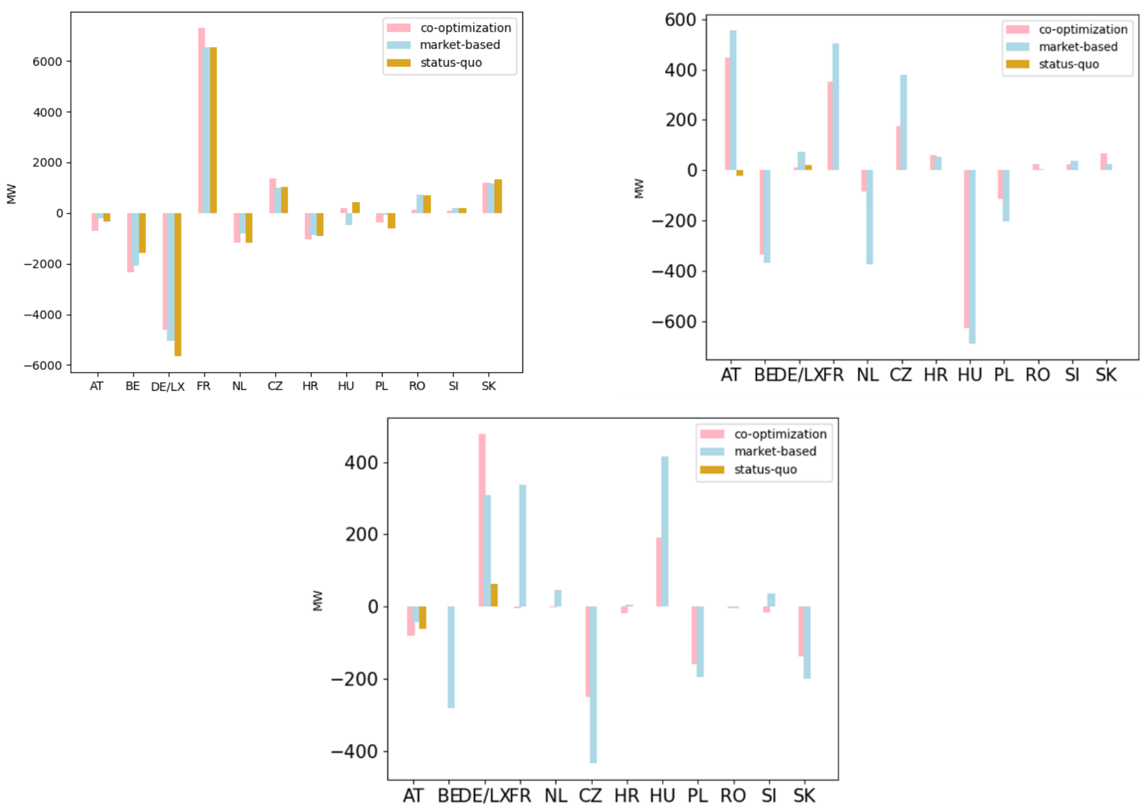


Figure 11: Upper left: upward (aFRR and mFRR) balancing capacity net position. Upper right: downward (aFRR and mFRR) balancing capacity net position. Bottom: energy net position.

5 Conclusions

The co-optimisation of energy and reserves can deliver coordination efficiencies that are driven by more efficient scheduling of power generation. We develop a modelling framework for quantifying these benefits and present a case study on the application of this framework to the Core region of Europe, which covers a geographic area with 594 GW of installed generation capacity.

We estimate that co-optimisation can deliver 678 million € per year of savings in operational costs for the Core region relative to the status quo of sequential clearing of balancing capacity followed by energy. The market-based allocation of Article 41 of EBGL achieves 84 million € per year relative to the status quo for the Core region. Extrapolating these figures to EU level (2670 TWh, compared to 1338 TWh of the Core region) indicates a potential cost saving of 1281 million € per year from co-optimisation relative to the status quo and a potential cost saving of 159 million € per year from market-based relative to the status quo.

The drivers for these efficiency gains relate to the misrepresentation of fixed costs in sequential designs, which result in an inefficient commitment of resources with relatively low fixed costs. Due to their technical minima, these resources replace inflexible lower-cost resources that could have been used instead in real time for serving forecast demand as well as imbalances. Co-optimisation avoids this pitfall by accounting for the fact that fixed costs are incurred once at the day-ahead stage for delivering both energy as well as balancing capacity, and selecting a mix of commitments in real time that is not constrained by rigidities related to technical minima and allows the system to rely as much as possible on inflexible low-marginal-cost resources.

The sequential clearing models rely heavily on intraday corrections. If such intraday corrections fail to materialise, we estimate an increase in the efficiency gains of co-optimisation relative to status quo to 1218 million € per year, with the market-based allocation of Article 41 of EBGL capturing 239 million € per year of savings relative to the status quo for the Core region.

Sequential designs rely on bidding opportunity costs for balancing capacity, and this can introduce errors in day-ahead scheduling in case of price forecast errors. This is especially so if one accounts for the appreciable price volatility that occurred in 2021 and 2022. Nevertheless, our modelling estimates that intraday corrections can largely absorb the adverse effect of these price forecast errors, to the extent that sequential designs with price forecast errors attain an average cost that is within the 95% confidence interval of the average cost of sequential designs without price forecast errors.

Our basic model has been used for a range of sensitivity analyses. In section G1 we analyse the effect of bidding opportunity costs explicitly in the day-ahead market under the co-optimisation design. Bidding opportunity costs is not necessary in co-optimised multi-product energy and balancing capacity auctions (in the same way that bidding for the opportunity cost of transmission explicitly is not necessary in co-optimised multi-product energy and transmission auctions). Doing so results in accounting for the opportunity costs of balancing capacity both in the objective function of the model as well as in the constraints of the market model, and thus in scheduling inefficiencies. Our modelling estimates these inefficiencies at approximately 100 million € per year in the Core region.

Appendix A: Acronyms

This appendix contains the list of acronyms that are used in the report.

ACER: European Union Agency for the Cooperation of Energy Regulators

aFRR: automatic Frequency Restoration Reserve

EBGL: Electricity Balancing Guideline

EUPHEMIA: EU Pan-European Hybrid Electricity Market Integration Algorithm

mFRR: manual Frequency Restoration Reserve

RR: Replacement Reserve

TSO: Transmission System Operator

Appendix B: Coordination inefficiencies

In section 2.2 we argue that fixed costs can result in a deviation of sequential market clearing from the co-optimisation outcome. This appendix provides a concrete example that illustrates this point.

We consider a system with 100 MW of inelastic load and 100 MW of balancing capacity requirements. Suppose that the system has two units. Unit G1 has a capacity of 210 MW, a marginal cost of 0 €/MWh, and a fixed cost of 1000 €. Unit G2 has a capacity of 100 MW, a marginal cost of 100 €/MWh and a fixed cost of 500 €.

The co-optimisation model commits unit G1 only. In the case of sequential market clearing, assuming that all agents compute their opportunity costs from equation (1) by anticipating a market clearing price of 0 €/MWh (the marginal cost of unit G1) in the energy market, both units G1 and G2 are committed. The same commitment occurs if agents anticipate a market clearing price of 100 €/MWh (the marginal cost of unit G2).

The erroneous commitment of units in the sequential design can be understood in terms of the error in committing unit G2 in the balancing capacity auction, where the lower fixed cost of unit G2 relative to unit G1 leads to the inefficient decision of committing unit G2 in the balancing capacity market. Instead, the co-optimisation model correctly anticipates that unit G1 can cover both energy and balancing capacity demand by incurring its slightly higher fixed cost but then benefitting from its lower marginal cost.

Appendix C: Nomenclature

The following nomenclature is used in the market clearing models that are presented in our study.

Sets

G: set of generators

Z: set of zones

$G(z)$: set of generators at zone z

$G_R(z)$: set of renewable generators at zone z

G_{fast}: set of fast generators

G_{slow}: set of slow generators

T_{15}: set of 15-minute time steps over a 24-hour horizon

T_{60}: set of hourly time steps over a 24-hour horizon

CB: set of critical branches

FZ_k: from zone of link k

TZ_k: to zone of link k

Variables

p_{gt}: power production of unit g

$p_{zt}^{R/PS}$: power production of hydro (R reservoir, PS pumped storage) at zone z

ds_{zt}: demand of pumped storage at zone z

$v_{zt}^{R/PS}$: hydro storage at zone z (R reservoir, PS pumped storage)

ls_t: load shedding at time period t

w_{gt}: commitment of unit g at time period t

z_{gt}: start-up of unit g at time period t

r_{zt}: net injection of energy at zone z at time period t

fr_{nt}: maximum flow of reserve on line n at time period t

$fr_{nt}^{+/-}$: upward/downward (+/-) flow of reserve on line n at time period t

$dr_z^{+/-}$: upward/downward (+/-) demand for reserve at zone z

nr_{zt}: upward/downward (+/-) net injection of reserve in zone z at time period t

$s_{gt}^{+mFRR/+aFRR}$: upward reserve allocation for unit g at period t

$s_{gt}^{-mFRR/-aFRR}$: downward reserve allocation for unit g at period t

Parameters

MC_g: marginal cost of generator g

K_g: no-load cost of generator g

S_g: start-up cost of generator g

PR_g: production of renewable generator g

D_{zt}: energy demand of zone z at time period t

$PTDF_{kz}$: power transfer distribution factor, zone z on link k

RAM_k: remaining available margin for link k

$A_{k,k'}$: parameter of contribution of reserve flow on link k' to flow on link k

$R_z^{mFRR/aFRR}$: reserve requirement for zone z

$R_z^{-mFRR/-aFRR}$: downward reserve requirement for zone z

P_g^+/P_g^-*:* technical maximum/minimum of generator g

R_g^+/R_g^-*:* ramp-up/down rate of generator g

$DT_z^{mFRR/aFRR}$*:* delivery time of the reserve products for zone z

UT_g/DT_g: minimum up/down time of unit g

$VOLL$: value of lost load

FZ_k/TZ_k: from-to zone of link k

μ: pumping efficiency

Appendix D: Technical details on methodology

Before describing the precise models that are used in our analysis in appendix E, we discuss certain methodological choices that we have adopted in our analysis.

D1 Sequence of decision-making

A basic methodological focus in our analysis is to capture the effect of lack of coordination on irrevocable decisions related to the physical commitment of units in the market. The following features are therefore central to our analysis: (i) the decisions of how units are scheduled (with a specific emphasis on unit commitment), and (ii) the sequential nature of interaction between day-ahead and balancing markets.

For the purpose of describing how units are scheduled, we resort to a unit-based unit commitment model. The goal here is to avoid any subjective assumptions on how units are aggregated into portfolios, since transparent data on portfolio offers is not available. Instead, there is available data on which units exist in the European system, and their precise location within bidding zones.

For the purpose of describing interactions between the day-ahead stage and the balancing market, we develop models for both stages. These models are linked through the irrevocable decisions of unit commitment. The balancing stage includes an explicit model of uncertainty in net demand, which is driven by renewable forecast errors.

As we explain in section 1.2, we focus our analysis on automatic frequency restoration reserve (aFRR) and manual frequency restoration reserve (mFRR). We distinguish between fast and slow units in our model. Both types of units are able to cover both aFRR and mFRR requirements. Fast units are able to adjust their commitment and dispatch in real time, whereas slow units can only adjust their dispatch in real time.

To give a more specific understanding of the precise structure of our modelling approach, we present an outline of the different models that are run in sequence in Figure 12. The day-ahead models (whether they describe co-optimisation or sequential market clearing) are complemented by a balancing energy module which aims at evaluating the quality of the commitment decisions over a set of real-time conditions, which correspond to a variety of renewable profiles. Concretely, the day-ahead models are solved using a forecast of renewable production which is expected to occur during the next day. This forecast typically deviates relative to the real-time production of renewable energy. Therefore, balancing capacity is introduced in the day-ahead market in order to react to the possible imbalances that emerge in real time. This relationship leads to a linkage between the day ahead and real time, which is depicted in Figure 12. The output of the day-ahead model is the commitment decisions of generators. The balancing energy model is then solved, and corresponds to an economic dispatch model for which the commitment of slow generators is fixed to the day-ahead commitment solution. We also fix units that are providing balancing capacity to remain on in real time. The dispatch of nuclear is also assumed to be fixed to its day-ahead level, in line with similar assumptions that have been adopted in past academic literature (Papavasiliou & Smeers, Remuneration of Flexibility using Operating Reserve Demand Curves: A Case Study of Belgium, 2017).

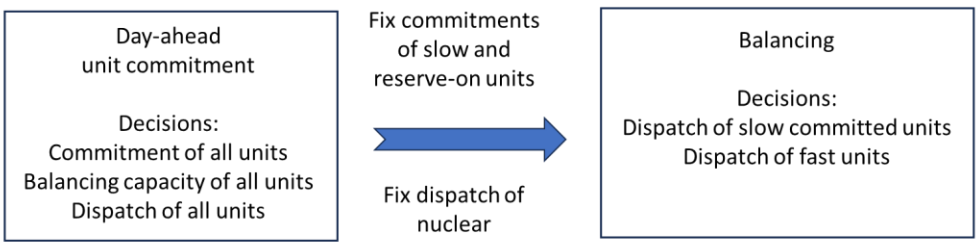


Figure 12: Linkage between the day-ahead and balancing energy models.

D2 Modelling sequential decisions

Sequential designs require an estimate of the opportunity cost of allocating generation capacity for the provision of balancing capacity instead of energy. This is depicted graphically in Figure 13.

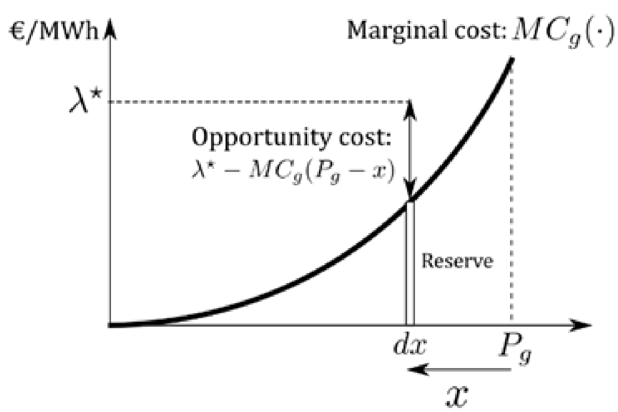


Figure 13: The opportunity cost of allocating balancing capacity is driven by the marginal cost of a unit as well as the anticipated energy price.

By allocating a slice of generation capacity dx to the balancing capacity market, instead of using it for selling energy at a price λ^*, we arrive to the opportunity cost of a generator g:

$$OC_g = \max(\lambda^* - MC_g, 0)$$

This opportunity cost is used in the objective function of the balancing capacity market models of the sequential designs, as we explain in sections E2 and E3.

D3 Price forecasts

A possible source of inefficiency in sequential market clearing is the fact that the opportunity costs described in section D2 may be computed using erroneous forecasts of energy market prices. We now describe how we model such forecasts.

Our starting point for price forecasts is the energy price that is computed from the co-optimisation model. To this we add a price forecast error. This forecast error is calculated as the randomly sampled difference between the energy price of historical day d and the energy price of the previous historical day of the same type for the year 2020[13]. In order to allow this forecast error to further vary between market participants, we introduce additional noise by randomly sampling from a zero-mean normal distribution with a standard deviation of 3% of the average day-ahead price.

D4 The deterministic requirement

As we explain in section 1.2, a novel aspect of our analysis is a linear approximation of the so-called deterministic requirement which guarantees that cross-zonal trades of balancing capacity do not overload the network. The challenging aspect of enforcing this requirement is that balancing capacity may or may not be activated in real time. We guarantee the deliverability of balancing capacity by using the following formulation, that ensures that the deterministic requirement is satisfied:

$$ne_z = \sum_{g \in G: Z_g = z} p_g - D_z$$

$$\sum_{z \in Z} ne_z = 0$$

[13] We perform a sensitivity analysis in section 4.2, where we use historical data from 2020-2022 instead of just 2020. Price volatility over these additional crisis years was significantly higher, and this sensitivity analysis allows us to quantify the sensitivity of our results on the magnitude of price forecast errors.

$$nr_z = \sum_{g \in G: Z_g = z} r_g - \sum_{l \in RL: Z_l = z} dr_l$$

$$nr_z = \sum_{k \in K: FZ_k = z} fr_k - \sum_{k \in K: TZ_k = z} fr_k, z \in Z$$

$$\sum_{z \in Z} PTDF_{zk} \cdot ne_z + \sum_{k' \in K} \max(A_{k,k'}, 0) \cdot fr_{k'} \leq RAM_k, k \in K$$

The non-trivial constraint is the last one, which is based on (Bemporad, Filippi, & Torrisi, 2004). The parameter $A_{k,k'}$ is defined as follows:

$$A_{k,k'} = PTDF_{FZ_{k'},k} - PTDF_{TZ_{k'},k}.$$

Appendix E: Technical details on models

In this section we describe the models that are used in our analysis.

E1 Co-optimisation model

We formulate the day-ahead co-optimisation model as follows:

$$\min \frac{1}{4} (\sum_{t \in T_{15}} \sum_{g \in G} MC_g p_{gt} + VOLL\ ls_t) + \sum_{t \in T_{60}} \sum_{g \in G} (K_g\ w_{gt} + S_g z_{gt}) \tag{E.1}$$

$$\sum_{g \in G(z)} p_{gt} + p_{zt}^{R} + p_{zt}^{PS} - ds_{zt} + \sum_{g \in G_R(z)} PR_{gt} + ls_{tz} - r_{zt} = D_{tz}, t \in T_{15}, z \in Z \tag{E.2}$$

$$\sum_{z \in Z} PTDF_{nz}\, r_{zt} + \sum_{n' \in CB} \max(A_{n,n'}, 0) \cdot fr_{n'} \leq RAM_n, t \in T_{15},\ n \in CB \tag{E.3}$$

$$\sum_{z \in Z} r_{zt} = 0, \qquad t \in T_{15} \tag{E.4}$$

$$dr_z^{-/+} = R_z^{-/+\,mFRR} + R_z^{-/+aFRR}, z \in Z \tag{E.5}$$

$$nr^{-/+}{}_{zt} = \sum_{g \in G(z)} s_{gt}^{-/+mFRR} + s_{gt}^{-/+aFRR} - dr_z^{-/+}, z \in Z, t \in T_{15} \tag{E.6}$$

$$nr^{-/+}{}_{zt} = \sum_{n \in CB: FZ_n = z} fr_{nt}^{-/+} - \sum_{n \in CB: TZ_n = z} fr_{nt}^{-/+}, z \in Z, t \in T_{15} \tag{E.7}$$

$$fr_{zt} = max(fr_{zt}^{-}, fr_{zt}^{+}), \qquad z \in Z, t \in T_{15} \tag{E.8}$$

$$\sum_{g \in G(z)} s_{gt}^{-/+aFRR} \geq R_z^{-/+aFRR}, z \in Z, t \in T_{15} \tag{E.9}$$

$$s_{gt}^{-/+mFRR} \leq \min\left(P_g^{+}, DT_z^{-/+mFRR} R_g^{-/+}\right), g \in G, t \in T_{15} \tag{E.10}$$

$$s_{gt}^{-/+aFRR} \leq \min\left(P_g^{+}, DT_z^{-/+aFRR} R_g^{-/+}\right), g \in G, t \in T_{15} \tag{E.11}$$

$$p_{gt} + s_{gt}^{+aFRR} \leq P_g^{+} w_{gt}, g \in G_{fast}, t \in T_{15} \tag{E.12}$$

$$p_{gt} + s_{gt}^{+mFRR} + s_{gt}^{+aFRR} \leq P_g^{+}, g \in G_{fast}, t \in T_{15} \tag{E.13}$$

$$p_{gt} + s_{gt}^{+mFRR} + s_{gt}^{+aFRR} \leq P_g^{+} w_{gt}, g \in G_{slow}, t \in T_{15} \tag{E.14}$$

$$p_{gt} - s_{gt}^{-mFRR} - s_{gt}^{-aFRR} \geq P_g^{-} w_{gt}, g \in G, t \in T_{15} \tag{E.15}$$

$$p_{gt} - p_{gt-1} + s_{gt}^{+mFRR} + s_{gt}^{+aFRR} \leq 15\, R_g^{+}, g \in G, t \in T_{15} \tag{E.16}$$

$$p_{gt-1} - p_{gt} + s_{gt}^{-mFRR} + s_{gt}^{-aFRR} \geq 15\, R_g^{-}, g \in G, t \in T_{15} \tag{E.17}$$

$$\sum_{q=t-UT_g+1}^{t} z_{gq} \leq w_{gt}, g \in G, t \geq UT_g \tag{E.18}$$

$$\sum_{q=t+1}^{t+Dt_g} z_{gq} \leq 1 - w_{gt}, g \in G, t \leq N - DT_g \tag{E.19}$$

$$z_{gt} \leq 1, g \in G, t \in T_{60} \tag{E.20}$$

$$z_{gt} \geq w_{gt} - w_{gt-1}, g \in G, t \in T_{60} \tag{E.21}$$

$$v_{zt}^{R} = v_{zt-1}^{R} - p_{zt}^{R}, z \in Z, t \in T_{15} \tag{E.22}$$

$$v_{zt}^{PS} = v_{zt-1}^{PS} + \mu\, d_{zt-1} - p_{zt}^{PS}, z \in Z, t \in T_{15} \tag{E.23}$$

$$p_{zt}^{R/PS} - p_{zt-1}^{R/PS} + s_{zt}^{+mFRR,\ R/PS} + s_{zt}^{+aFRR,\ R/PS} \leq 15\, R_{R/PS}^{+}, z \in Z, t \in T_{15} \tag{E.24}$$

$$p_{zt-1}^{R/PS} - p_{zt}^{R/PS} + s_{zt}^{-mFRR,\ R/PS} + s_{zt}^{-aFRR,\ R/PS} > 15\, R_{R/PS}^{-}, z \in Z, t \in T_{15} \tag{E.25}$$

$$ds_{zt} - ds_{zt-1} + s_{zt}^{-mFRR,\ R/PS} + s_{zt}^{-aFRR,\ R/PS} \leq 15\, R_{R/PS}^{+}, z \in Z, t \in T_{15} \tag{E.26}$$

$$ds_{zt-1} - ds_{zt} + s_{zt}^{+mFRR,\ R/PS} + s_{zt}^{+aFRR,\ R/PS} \geq 15\, R_{R/PS}^{-}, z \in Z, t \in T_{15} \tag{E.27}$$

$$p_{gt}, p_{zt}^{R/PS}, v_{zt}^{R/PS}, ds_{zt}, z_{gt}, s_{gt}, ls_t \geq 0, w_{gt} \in \{0,1\} \tag{E.28}$$

Eq. (E.1) describes the objective function of the co-optimisation model. This cost function consists of the production cost of units, the cost for not serving demand[14], no-load cost[15] and start-up costs. The net injection of energy is defined in constraint (E.2). Constraints (E.3) model the flow-based polytope as well as the deterministic requirement of section D4. Note that, in the second term of the flow constraint (E.3), we model the effect of the trade of balancing capacity on occupying cross-zonal capacity. Constraint (E.4) corresponds to energy balance, which is expressed as the fact that the total net injection of energy throughout the network balances out. Constraint (E.5) describes the demand for frequency restoration reserve as the sum of an inelastic requirement for aFRR and an inelastic requirement for mFRR. Constraint (E.6) defines a variable which quantifies the net injection of balancing capacity at each market area. This variable is needed for the formulation of the deterministic requirement for trading balancing capacity. Constraint (E.7) links the injection of balancing capacity to the flow of balancing capacity over the network, which is needed for expressing the deterministic requirement of section D4. Constraint (E.8) imposes that the flow in the line should be allocated as the maximum between upward and downward (as to avoid netting the quantities). The market clearing constraint for the aFRR market is modelled through constraint (E.9). Constraints (E.10) and (E.11) model the effect of ramp rate on the ability of units to deliver balancing capacity. Constraints (E.12)-(E.15) model the technical generation capabilities of the units. Here, we assume that fast generators can offer mFRR even if they are offline. This is achieved by constraint (E.13). Instead, constraint (E.12) enforces that offering aFRR requires that fast units should be committed. Constraint (E.14) enforces the maximum generation capacity limit for slow units and constraint (E.15) imposes the minimum generation limits for all generators. Constraints (E.16)-(E.17) model the ramp up/down capabilities. Constraints (E.18)-(E.21) model the start-up and minimum up/down times of the generators. These constraints correspond to the convex hull of minimum up/down time polytopes in the absence of ramp constraints (Rajan & Takriti, 2005), and therefore enable the mixed integer programming solvers that are used in our work to converge more quickly since they tend to produce tighter bounds in the linear programming relaxation of the unit commitment problem. Finally, constraints (E.22)-(E.27) model the reservoirs and pumped

[14] Following (Papavasiliou & Smeers, Remuneration of Flexibility using Operating Reserve Demand Curves: A Case Study of Belgium, 2017), VOLL is assumed to be equal to 3000 €/MWh for all bidding zones.

[15] No-load cost is a cost that is incurred at every period that a unit is online that is not related to the fuel cost for producing at the technical minimum of a unit. The cost that a unit incurs for operating at its technical minimum is accounted for separately in our model through constraints (E.15) and the first term of the objective function.

storage. Constraints (E.22)-(E.23) model the reservoirs and the energy balance of the storage, while constraints (E.24)-(E.27) model the ramp-up and down capabilities.

We compute day-ahead energy prices through integer programming pricing (O'Neill, Sotkiewicz, Hobbs, Rothkopf, & Stewart, 2005). Concretely, the co-optimisation model (E.1)-(E.21) is solved, and the optimal solution for the commitment variables w_{gt} and z_{gt} is retrieved. The binary variables are then fixed, and the model is re-run in order for prices to be computed. The day-ahead energy prices are then calculated as the dual multiplier of constraint (E.2) in this pricing re-run.

E2 Status quo

We now proceed to describe the status quo design. The first step in this design is to clear a market that trades balancing capacity. We model this balancing capacity market as follows:

$$\min \frac{1}{4} \sum_{t \in T_{15}} \sum_{g \in G} OC_{gt}\left(s_{gt}^{+mFRR} + s_{gt}^{+aFRR}\right) + \sum_{t \in T_{60}} \sum_{g \in G} \left(C_g\left(P_g^{-} + s_{gt}^{-mFRR} + s_{gt}^{-aFRR}\right) w_{gt} + K_g w_{gt} + S_g z_{gt}\right) \tag{E.29}$$

$$s_{gt}^{-/+mFRR} \leq \min\left(P_g^{+}, DT_z^{mFRR} R_g^{-/+}\right), g \in G, t \in T_{15} \tag{E.30}$$

$$s_{gt}^{-/+aFRR} \leq \min\left(P_g^{+}, DT_z^{aFRR} R_g^{-/+}\right), g \in G, t \in T_{15} \tag{E.31}$$

$$\sum_{g \in G(z)} s_{gt}^{-/+aFRR} \geq R_z^{-/+aFRR}, z \in Z \tag{E.32}$$

$$\sum_{g \in G(z)} s_{gt}^{-/+aFRR} + s_{gt}^{-/+mFRR} \geq R_z^{-/+aFRR} + R_z^{-/+mFRR}, z \in Z \tag{E.33}$$

$$P_g^{-} w_{gt} + s_{gt}^{+aFRR} \leq P_g^{+} w_{gt}, g \in G_{fast}, t \in T_{15} \tag{E.34}$$

$$P_g^{-} + s_{gt}^{+mFRR} + s_{gt}^{+aFRR} \leq P_g^{+}, g \in G_{fast}, t \in T_{15} \tag{E.35}$$

$$P_g^{-} w_{gt} + s_{gt}^{+mFRR} + s_{gt}^{+aFRR} \leq P_g^{+} w_{gt}, g \in G_{slow}, t \in T_{15} \tag{E.36}$$

$$s_{gt}^{-/+mFRR} + s_{gt}^{-/+aFRR} \leq 15\, R_g^{-/+}, g \in G, t \in T_{15} \tag{E.37}$$

$$\sum_{q=t-UT_g+1}^{t} z_{gq} \leq w_{gt} \tag{E.38}$$

$$\sum_{q=t+1}^{t+Dt_g} z_{gq} \leq 1 - w_{gt}\,, g \in G, t \leq N - DT_g \tag{E.39}$$

$$z_{gt} \leq 1, g \in G, t \in T_{60} \tag{E.40}$$

$$z_{gt} \geq w_{gt} - w_{gt-1}, g \in G, t \in T_{60} \tag{E.41}$$

$$\widehat{p_{zt}^{R/PS}} - \widehat{p_{zt-1}^{R/PS}} + s_{zt}^{+mFRR,\ R/PS} + s_{zt}^{+aFRR,\ R/PS} \leq 15\ R_{R/PS}^{+}, z \in Z, t \in T_{15} \tag{E.42}$$

$$\widehat{p_{zt-1}^{R/PS}} - \widehat{p_{zt}^{R/PS}} + s_{zt}^{-mFRR,\ R/PS} + s_{zt}^{-aFRR,\ R/PS} > 15\ R_{R/PS}^{-}, z \in Z, t \in T_{15} \tag{E.43}$$

$$\widehat{ds_{zt}} - \widehat{ds_{zt-1}} + s_{zt}^{-mFRR,\ R/PS} + s_{zt}^{-aFRR,\ R/PS} \leq 15\ R_{R/PS}^{+}, z \in Z, t \in T_{15} \tag{E.44}$$

$$\widehat{ds_{zt-1}} - \widehat{ds_{zt}} + s_{zt}^{+mFRR,\ R/PS} + s_{zt}^{+aFRR,\ R/PS} \geq 15\ R_{R/PS}^{-}, z \in Z, t \in T_{15} \tag{E.45}$$

$$z_{gt}, s_{gt} \geq 0, w_{gt} \in \{0,1\} \tag{E.46}$$

The objective function, described in equation (E.29), is composed of the opportunity cost of booking balancing capacity in the balancing capacity market, plus certain fixed costs related to the commitment of a generator. These fixed costs include the cost that a unit incurs for operating at its technical minimum $C_g(P_g^- + s_{gt}^{-mFRR} + s_{gt}^{-aFRR})\, w_{gt}$ (note that the downward reserve implies a higher minimal production), no-load cost $K_g\, w_{gt}$, and startup cost $S_g z_{gt}$. Constraints (E.30)-(E.31) limit the amount of balancing capacity that can be made available by a unit by taking into account the ramp specifications of the generators. Constraints (E.32)-(E.33) define the balancing capacity requirements for both aFRR and mFRR, and capture the effect of one-way substitutability, whereby fast units can satisfy the needs of all balancing capacity products, whereas slow units can only cover mFRR needs. Constraints (E.34)-(E.41) relate to technical capabilities of the units. Equations (E.34)-(E.37) constrain the amount of balancing capacity that can be provided by taking into account the min/max generation capabilities of the generators. Furthermore, these equations encode the assumption that fast generators can offer mFRR even if they are offline. Constraints (E.38)-(E.41) model the start-up, and min up/down times of the generators. The balancing capacity provided by hydro is modelled with constraints (E.42)-(E.45). The balancing capacity module cannot optimise the hydro production profiles, thus the production/demand profiles $p_{zt-1}^{R/PS}, p_{zt-1}^{R/PS}$ are fixed to historical values.

Note that this is an optimistic model of sequential market clearing, because it is unit-based, and it is richer than the bidding language that is available in existing European balancing capacity markets. Specifically, existing balancing capacity markets do not account for min up/down time constraints or fixed commitment costs of individual units, and it is rather up to the portfolio owners to translate these physical constraints and costs to bidding products that balancing markets accept. On the other hand, portfolio owners in certain markets can trade their positions or disaggregate market outcomes into nominations of individual physical units, which can rationalise our optimistic modelling of the balancing capacity market to a certain extent. Another reason why the model is optimistic is because it considers the co-optimised trading of aFRR and mFRR, whereas the trading of these two interacting balancing capacity products is typically decoupled in existing designs and will likely continue to be decoupled in the actual implementation of the market-based approach, thereby introducing further inefficiencies.

The energy market clearing model trades energy while fixing the allocation of balancing capacity to the solution that is obtained in the balancing capacity market model. Following a similar description as in the co-optimisation model, the mathematical model is described as follows.

$$\min \frac{1}{4}\Big(\sum_{t \in T_{15}} \sum_{g \in G} MC_g p_{gt} + VOLL\ ls_t\Big) + \sum_{t \in T_{60}} \sum_{g \in G} (K_g\ w_{gt} + S_g z_{gt}) \tag{E.47}$$

$$\sum_{g \in G(z)} p_{gt} + p_{zt}^{R} + p_{zt}^{PS} + \sum_{g \in G_R(z)} PR_{gt} + ls_{tz} - r_{zt} = D_{tz}, t \in T_{15}, z \in Z \tag{E.48}$$

$$\sum_{z \in Z} PTDF_{nz}\, r_{zt} \leq RAM_n, t \in T_{15},\ n \in CB \tag{E.49}$$

$$\sum_{z \in Z} r_{zt} = 0, t \in T_{15} \tag{E.50}$$

$$p_{gt} + \bar{s}_{gt}^{aFRR} \leq P_g^{+} w_{gt}, g \in G_{fast}, t \in T_{15} \tag{E.51}$$

$$p_{gt} + \bar{s}_{gt}^{mFRR} + \bar{s}_{gt}^{aFRR} \leq P_g^{+}, g \in G_{fast}, t \in T_{15} \tag{E.52}$$

$$p_{gt} + \bar{s}_{gt}^{mFRR} + \bar{s}_{gt}^{aFRR} \leq P_g^{+} w_{gt}, g \in G_{slow}, t \in T_{15} \tag{E.53}$$

$$p_{gt} \geq P_g^{-} w_{gt}, g \in G, t \in T_{15} \tag{E.54}$$

$$p_{gt} - p_{gt-1} + \bar{s}_{gt}^{mFRR} + \bar{s}_{gt}^{aFRR} \leq 15\ R_g^{+}, g \in G, t \in T_{15} \tag{E.55}$$

$$p_{gt-1} - p_{gt} \geq 15\ R_g^{-}, g \in G, t \in T_{15} \tag{E.56}$$

$$\sum_{q=t-UT_g+1}^{t} z_{gq} \leq w_{gt}, g \in G, t \geq UT_g \quad \text{(E.57)}$$

$$\sum_{q=t+1}^{t+Dt_g} z_{gq} \leq 1 - w_{gt}, g \in G, t \leq N - DT_g \quad \text{(E.58)}$$

$$z_{gt} \leq 1, g \in G, t \in T_{60} \quad \text{(E.59)}$$

$$z_{gt} \geq w_{gt} - w_{gt-1}, g \in G, t \in T_{60} \quad \text{(E.60)}$$

$$v_{zt}^{R} = v_{zt-1}^{R} - p_{zt}^{R}, z \in Z, t \in T_{15} \quad \text{(E.61)}$$

$$v_{zt}^{PS} = v_{zt-1}^{PS} + \mu\, d_{zt-1} - p_{zt}^{PS}, z \in Z, t \in T_{15} \quad \text{(E.62)}$$

$$p_{zt}^{R/PS} - p_{zt-1}^{R/PS} + \bar{s}_{zt}^{+mFRR,\ R/PS} + \bar{s}_{zt}^{+aFRR,\ R/PS} \leq 15\ R_{R/PS}^{+}, z \in Z, t \in T_{15} \quad \text{(E.63)}$$

$$p_{zt-1}^{R/PS} - p_{zt}^{R/PS} + \bar{s}_{zt}^{-mFRR,\ R/PS} + \bar{s}_{zt}^{-aFRR,\ R/PS} > 15\ R_{R/PS}^{-}, z \in Z, t \in T_{15} \quad \text{(E.64)}$$

$$ds_{zt} - ds_{zt-1} + \bar{s}_{zt}^{-mFRR,\ R/PS} + \bar{s}_{zt}^{-aFRR,\ R/PS} \leq 15\ R_{R/PS}^{+}, z \in Z, t \in T_{15} \quad \text{(E.65)}$$

$$ds_{zt-1} - ds_{zt} + \bar{s}_{zt}^{+mFRR,\ R/PS} + \bar{s}_{zt}^{+aFRR,\ R/PS} \geq 15\ R_{R/PS}^{-}, z \in Z, t \in T_{15} \quad \text{(E.66)}$$

$$p_{gt}, z_{gt}, ls_t \geq 0, w_{gt} \in \{0,1\} \quad \text{(E.67)}$$

Model (E.47)-(E.67) follows a similar structure to that of the co-optimisation model, with the difference that the balancing capacity variables ($\bar{s}_{gt}^{-/+mFRR}$ and $\bar{s}_{gt}^{-/+aFRR}$) are fixed to the solution of the balancing capacity market model. Furthermore, note that the flow-based polytope described by constraint (E.49) does not consider the trade of balancing capacity.

E3 Market based allocation

The market-based model follows the same structure as that of the status quo model of section E2. In this section we limit ourselves to describing the differences between the two models.

Firstly, in the balancing capacity market model of the market-based approach we allow the day-ahead exchange of balancing capacity between bidding zones and for this reason we introduce the deterministic requirement of section D4. Moreover, following Article 41(2) of the European Balancing Guideline (European Commission, 2017), we introduce a 10% limit on the amount of cross-zonal capacity that can be allocated for the exchange of balancing capacity between cross-border lines.

Additionally, in the day-ahead energy market model, the deterministic requirement appears in the flow-based constraints, where the amount of balancing capacity that is traded is fixed to the solution of the day-ahead balancing capacity market. This encodes the fact that day-ahead cross-zonal network capacity that is allocated for the exchange of balancing capacity cannot be double-booked for the exchange of day-ahead energy.

E4 Balancing market

As we describe in section D1, the day-ahead model is complemented by a real-time balancing energy module. Within this module, we follow the mathematical description of the co-optimisation model (E.1)-(E.28), with a few modifications that we describe below.

There are no balancing capacity requirements, thus equations (E.5)-(E.9) are not considered. Furthermore, the variables $s_{gt}^{mFRR/aFRR}$ are set to zero in the balancing energy model.

The flow-based polytope described by constraint (E.3) does not include trade of reserve, since cross-zonal capacity is already allocated in the day-ahead market, thus it is replaced by:

$$\sum_{z \in Z} PTDF_{nz}\, r_{zt} \leq RAM_n, t \in T_{15},\ n \in CB$$

The commitment w_{gt} of the slow generators is fixed to the day-ahead commitment.

A stochastic parameter is introduced in the energy balance constraint (E.2), which corresponds to a variety of real-time renewable production profiles:

$$\sum_{g \in G(z)} p_{gt} + p_{zt}^{R} + p_{zt}^{PS} - ds_{zt} + \sum_{g \in G_R(z)} PR_{gt}(\omega) + ls_{tz} - r_{zt} = D_{tz} \quad (\lambda_{tz}), t \in T_{15}, z \in Z$$

The real-time module is run repeatedly using a different realisation of the uncertain parameters based on the state of the world ω at each sample. The results of the balancing energy market model are those that are used for quantifying the efficiency of the different designs, since it represents the actual physical operation of the system.

Appendix F: Technical details on case study

We analyse the Core region of Europe in our study. In this section we describe how the data is assembled, and we discuss some characteristics of the system.

F1 Generator data

The technical characteristics of different technologies (min up and down times, ramp rates, technical minima and maxima, startup costs, min load costs, and heat rate curves) are based on an industrial database of thermal generators, which has been provided to our group by industrial partners. The installed capacity for each technology is presented in Table 2. The installed capacity and number of units per technology and per country is based on the ENTSO-E transparency platform.

	Fast (MW)	Slow (MW)	Non-dispatchable (MW)	Total (MW)	Marginal cost	Fixed cost
Biomass	10892	1142	0	12034	Medium	Medium
Gas	75747	11981	0	87728	High	Medium
Hard coal	0	46511	0	46511	High	High
Waste	729	845	0	1574	Medium	Low
Nuclear	0	0	82087	82087	Low	High
Brown coal/lignite	0	38281	0	38281	High	High
Oil	5934	752	0	6685	High	Medium
Coal-derived gas	2331	0	0	2331	High	Medium
Hydraulic pumped storage	22960	0	0	22960	N/A	N/A
Wind	0	0	119084	119084	Low	Low
Hydraulic run of river	0	0	27246	27246	N/A	N/A
Hydraulic reservoir	19273	0	0	19273	N/A	N/A
Solar	0	0	128553	128553	Low	Low

Table 2: Total capacity of each technology and part of each technology that is classified as fast or slow.

The capacity of thermal generators within Germany, France and Belgium was reduced in order to account for scheduled maintenance and large outages. A different outage derating factor was computed for each generator and each season. These are computed based on outage duration and frequency information for each generator.

Table 2 presents the technologies and their classification between fast, slow and other. Technologies that are neither fast nor slow are non-dispatchable, in the sense that their dispatch is fixed to the result of the day-ahead market model. Table 3 presents the breakdown of each technology per bidding zone.

	AT	BE	HR	CZ	FR	DE/LU	HU	NL	PL	RO	SI	SK	Total
Biomass	766	725	56	365	1300	7179	231	632	659	121	0	0	12034
Gas	4194	6846	822	1247	11628	31776	3715	18200	3870	2031	769	2630.0	87728
Hard coal	0	0	217	1267	1760	17942	42	4061	21052	169	0	0	46511
Waste	109	106	0	94	0	556	39	642	0	0	29	0	1574
Nuclear	0	5936	0	3936	60782	4121	1916	479	0	1300	696	2921	82087
Brown coal/lignite	0	0	0	7177	0	17598	1164	0	8299	2545	1278	220	38281
Oil	355	228	43	0	2475	2699	432	0	404	0	48	0	6685
Coal-derived gas	0	305	0	375	422	957	0	0	272	0	0	0	2331
Hydraulic pumped storage	3363	1308	281	1172	5051	9280	0	0	1591	0.0	180	734	22960
Wind	3569	5315	981	339	21336	65871	323	9410	8978	2957	2	3	119084
Hydraulic run of river	5902	186	428	340	11695	3737	33	0	323	2780	1102	720	27246
Hydraulic reservoir	2771	0.0	1446	772	8787	1444	28	0	469	3356	0.0	200	19273
Solar	3265	6475	140	2083	14639	63366	3300	22590	10643	1185	294	573	128553
Total	24295	27244	4414	19167	139875	226526	11223	56051	56560	16444	4398	8001.4	594.347

Table 3: Installed capacity per Member State. All values are in MW.

F2 Day types

Certain input data (such as demand, renewable supply data, and hydrology) are time-varying in our analysis. Thus, we describe a typical year of operation by considering eight representative days. The day types distinguish between weekends (WE) and weekdays (WD), as well as by season, thus leading to eight day types: spring WD/WE, summer WD/WE, autumn WD/WE, and winter WD/WE. We use clustering to select these representative day types.

F3 Network data

The network model used in this paper is a flow-based model based on zonal PTDFs. To deliver a model that is as realistic as possible, the polytope that is considered corresponds to the flow-based polytope that is used in actual operations. This data is publicly available online through the JAO website[16]. To each day type we assign a flow-based polytope by randomly selecting a day that belongs to the day type in question and selecting the corresponding polytope. Table 4 specifies the exact date that has been selected for representing each day type.

Day type	**Date**
Spring WD	15/02/2023
Spring WE	20/05/2023
Summer WD	12/06/2023
Summer WE	30/06/2023
Autumn WD	11/10/2023
Autumn WE	04/11/2023
Winter WD	11/01/2023
Winter WE	18/02/2023

Table 4: Source date of PTDF polytope corresponding to each day type.

F4 Load and renewables

The installed capacity for solar, wind and hydro power is collected from the ENTSO-E transparency platform for the year 2023. The normalised time series of renewable supply (which include real-time samples) are based on (Aravena & Papavasiliou, Renewable Energy Integration in Zonal Markets, 2017). Using this data, we are able to generate 145 profiles of renewable supply data. These samples are the input that is used in the real-time balancing market simulations. On the other hand, the day-ahead simulations are run using the average renewable supply data.

[16] https://publicationtool.jao.eu/core/finalComputation

F5 Reserve requirements

Reserve requirements are sourced from diverse sources, including publicly available sources and communication with national regulators and TSOs. The reserve requirements are presented in Table 5.

	aFRR up	aFRR down	mFRR up	mFRR down
Austria (AT)	200	200	280	195
Belgium (BE)	117	117	920	877
Croatia (HR)	75	75	242	130
Czechia (CZ)	154	164	844	206
France (FR)	728	728	1000	0
Germany/Luxembourg (DE/LU)	1800	1800	600	400
Hungary (HU)	250	331	123	1100
Netherlands (NL)	350	350	954	726
Poland (PL)	627	627	1500	1300
Romania (RO)	316	316	1400	870
Slovakia (SK)	130	130	510	239
Slovenia (SI)	65	60	190	20

Table 5: Reserve requirements per bidding zone. Units are in MW.

Appendix G: Sensitivity analyses

This section provides additional information on the results of our analysis, including a barrage of sensitivity analyses that were inspired by discussions with ACER.

Before proceeding to the discussion of the additional sensitivity analyses, we discuss some aspects related to the computational performance of our models. The computational times are as follows: (i) the day-ahead co-optimisation requires approximately 1 hour of run time per day type, (ii) the day-ahead sequential clearing model requires approximately half an hour of run time per day type, and (iii) the real-time economic dispatch model requires approximately two minutes of run time per sample. The runs have been carried out in ARIS on the GRNET cluster in Greece, which consists of 532 computational nodes, separated into four node categories. The runs have been performed on the thin nodes of the cluster, which consists of 426 computing nodes and a total of 8520 cores. Each node consists of two Ivy Bridge-Intel Xeon E5-2680v2 processors, each one equipped with 10 cores. The optimisation software that is used for the analysis is Gurobi 10.3.

G1 Internalizing opportunity costs in co-optimisation

It is interesting to note that one desire expressed by certain market participants in the policy debate surrounding a transition to co-optimisation is to maintain the option of bidding explicit balancing capacity costs in the co-optimised multi-product auction. This makes little sense from the economic standpoint of expressing opportunity costs, because opportunity costs are already accounted for endogenously in the multi-product auction. Nevertheless, it is a practice that is actually encountered in certain systems, e.g. the integrated scheduling process of the electricity market in Greece and Cyprus. In our analysis, we represent the opportunity costs of balancing capacity, as computed for the sequential market designs, as an explicit cost in the objective function of the co-optimisation model.

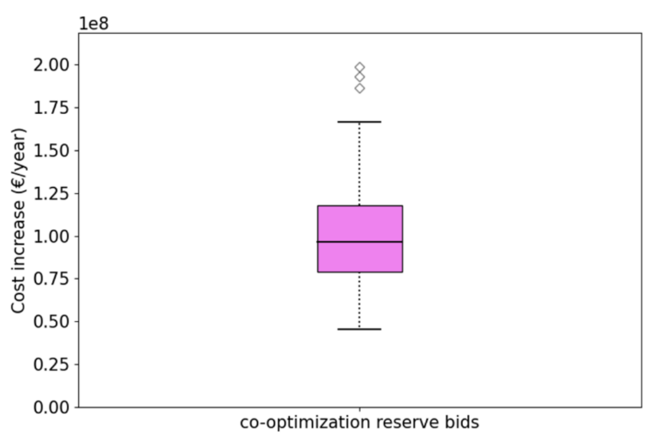
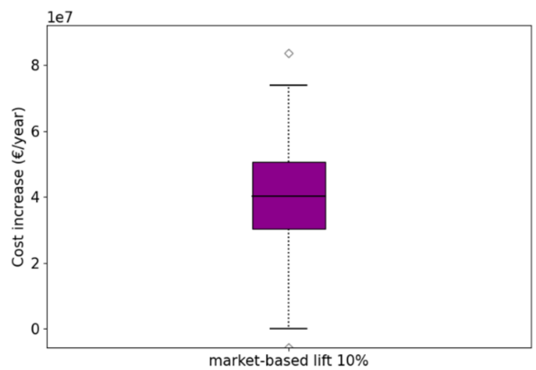


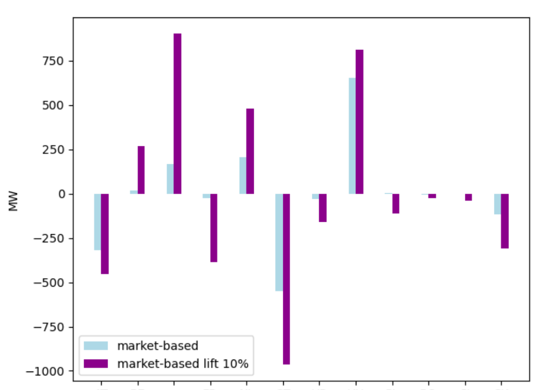
Figure 14: Cost increase in real-time operations when introducing explicit balancing capacity costs in the co-optimisation model.

The results of this analysis are presented in Figure 14, where we record the cost increase of real-time operations when introducing explicit opportunity costs. Concretely, we observe a relative average cost increase of approximately 0.3% with respect to the co-optimisation setting without explicit reserve bidding. This deterioration in performance is not surprising. In principle, explicit balancing capacity costs in a co-optimisation model should allow generators to express economic costs that are related to the provision of balancing capacity alone, and are not variable or fixed (min load, no-load and startup) costs. No such costs exist in our analysis, and introducing opportunity costs explicitly in the co-optimisation model means that they are accounted for twice in the day-ahead auction (once as explicitly costs in the objective function and then again through constraints in the market model), and thus lead to inefficient day-ahead commitment decisions.

G2 Lifting the 10% limit in the market-based approach

The increased trading that is allowed by the co-optimisation model is closely linked to the fact that the co-optimisation model is not subject to a 10% limit on the allocation of cross-zonal capacity for the purpose of trading balancing capacity. This motivates the question of whether the 10% limit is driving the inefficiencies of the market-based design by inefficiently eliminating opportunities for trading balancing capacity. The left panel of Figure 15 actually establishes that lifting the 10% limit would actually backfire for the market-based approach, by increasing inefficiencies by 39 million € per year for the Core region. Erring on the safe side by not allocating too much cross-zonal capacity for the trade of balancing capacity turns out to be preferable to erring on the opposite side, since lifting the 10% limit is observed to deprive the day-ahead energy market from an excessive amount of cross-zonal transmission capacity. The right panel of Figure 15 depicts the net position of each bidding zone in the market-based approach before and after lifting the 10% limit on the allocation of cross-zonal capacity for the exchange of balancing capacity.





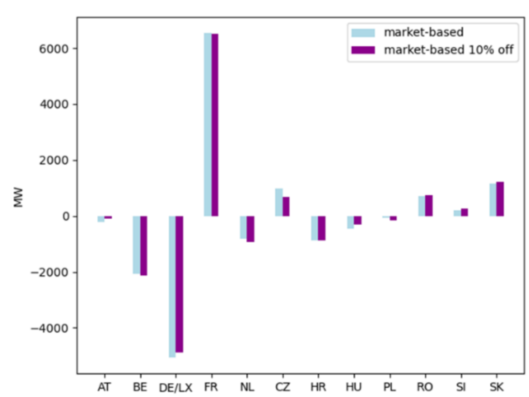


Figure 15: Up: daily cost increase if we lift the 10% limit on the allocation of cross-zonal capacity for the trade of balancing capacity in the market-based approach. Lower left [right]: net balancing capacity [energy] position of each bidding zone in the market-based approach before and after lifting the 10% limit on the allocation of cross-zonal capacity for the exchange of balancing capacity.

G3 Welfare benefits of Austrian-German aFRR cooperation

The Austrian-German aFRR cooperation initiative has been put in place in February 2020, and has allowed the German and Austrian TSOs to share 80 MW of aFRR on the DE-AT border, in both directions. The savings that have been estimated by ENTSO-E[17] from this sharing amount to 17 million € per year. The estimate of the savings based on our real-time model is 22 million € per year, as indicated in Figure 16. Although the methodologies used for these estimations are different, the savings seem to be in the same range. Note that our model accounts for both aFRR and mFRR, whereas ENTSO-E focuses on aFRR only and estimates are based on the effect of the measure on the day-ahead market.

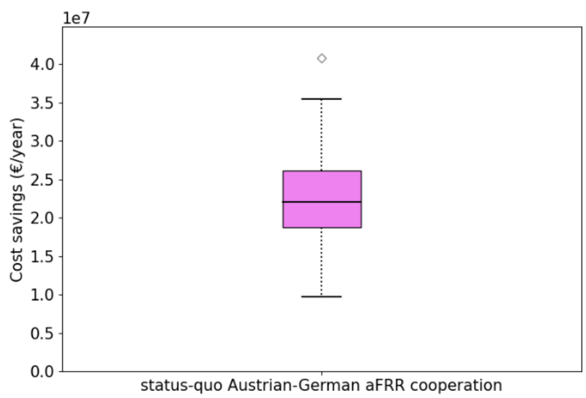


Figure 16: Cost savings (in € per year) of the Austrian-German aFRR cooperation initiative as estimated by our model.

G4 Sensitivity on the nuclear power availability of France

One of the drivers of efficiency gains within the co-optimisation design is the higher usage of nuclear power, particularly in France, as compared to the sequential designs (see the welfare analysis, subsection 4.2). In this section we consider a sensitivity analysis where French nuclear power capacity is reduced to levels that correspond to the historically documented amount of nuclear power production in 2023, which was significantly lower than the nominal

[17] https://ee-public-nc-downloads.azureedge.net/strapi-test-assets/strapi-assets/2022_ENTSO_E_Balancing_Report_Web_2bddb9ad4f.pdf, section 3.2.2.2.

capacity of nuclear technology in our model. The welfare gains of this sensitivity analysis are presented in Figure 17. We observe that, although there is a reduction in welfare benefits, it is rather low. In fact, the welfare reduction represents 0.3% of the efficiency gains of co-optimisation in the base case scenario.

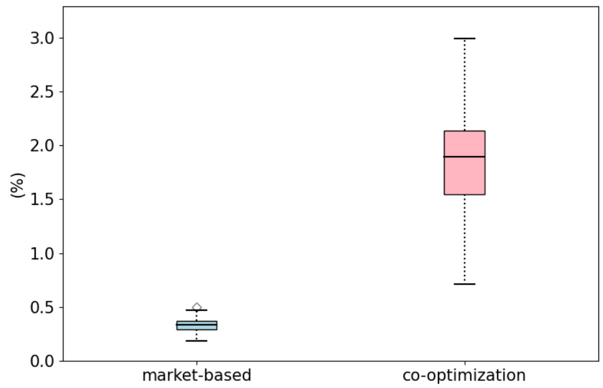


Figure 17: Welfare comparison of alternative designs in the case of outage in French nuclear power plants, corresponding to historical conditions in 2023. The figure presents the relative cost comparison of the co-optimisation and market-based approach relative to status-quo.

References

Ahlqvist, V., Holmberg, P., & Tangerås, T. P. (2018). *Central-versus self-dispatch in electricity markets.* Cambridge, UK: University of Cambridge, Faculty of Economics.

Aravena, I., & Papavasiliou, A. (2017). Renewable Energy Integration in Zonal Markets. *IEEE Transactions on Power Systems, 32*(2), 1334-1349.

Aravena, I., Lété, Q., Papavasiliou, A., & Smeers, Y. (2021). Transmission capacity allocation in zonal electricity markets. *Operations Research, 69*(4), 1240-1255.

Bemporad, A., Filippi, C., & Torrisi, F. D. (2004). Inner and outer approximations of polytopes using boxes. *Computational Geometry, 27*(2), 151-178.

Chen, Y., Gribik, P., & Gardner, J. (2014). Incorporating post zonal reserve deployment transmission constraints into energy and ancillary service co-optimization. *IEEE Transactions on Power Systems, 29*(2), 537-549.

Doorman, G. L., & Van Der Veen, R. (2013). An analysis of design options for markets for cross-border balancing of electricity. *Utilities Policy, 27*, 39-48.

ENTSO-E. (2021). *Implementation impact assessment for the methodology for a co-optimised allocation process of cross-zonal capacity for the exchange of balancing capacity or sharing of reserves.* Brussels, Belgium: ENTSO-E.

European Commission. (2017). *Commission Regulation (EU) 2017/1485 of 2 August 2017 establishing a guideline on electricity transmission system operation.* Brussels, Belgium: European Commission.

European Commission. (2017). *Commission regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing.* Brussels, Belgium: European Commission.

Kunz, F. (2013). Improving congestion management: how to facilitate the integration of renewable generation in Germany. *The Energy Journal, 34*(4).

Nohadani, O., & Kartikey, S. (2018). Optimization under decision-dependent uncertainty. *SIAM Journal on Optimization, 28*(2), 1773-1795.

N-SIDE. (2022). *Co-Optimization of Energy and Balancing Capacity in the European Single Day-Ahead Coupling.* Louvain la Neuve, Belgium: N-SIDE.

N-SIDE; AFRY. (2020). *CZC allocation with co-optimization.* Louvain la Neuve, Belgium: November.

O'Neill, R. P., Sotkiewicz, P. M., Hobbs, B. F., Rothkopf, M. H., & Stewart, W. R. (2005). Efficient market-clearing prices in markets with nonconvexities. *European journal of operational research, 164*(1), 269-285.

Oren, S. (2001). Design of Ancillary Service Markets. *Proceeding of the 34th Hawaii International Conference on Systems Sciences HICSS 34.* Maui, Hawaii: HICSS.

Papavasiliou, A., & Oren, S. (2013, May/June). Multi-Area Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network. *Operations Research, 61*(3), 578-592.

Papavasiliou, A., & Smeers, Y. (2017). Remuneration of Flexibility using Operating Reserve Demand Curves: A Case Study of Belgium. *The Energy Journal, 38*.

Rajan, D., & Takriti, S. (2005). *Mininum Up/Down Polytopes of the Unit Commitment Problem with Startup Costs.* New York: IBM Research.

Ruiz, P. A., Philbrick, R. C., & Sauer, P. W. (2009). Modeling approaches for computational cost reduction in stochastic unit commitment formulations. *IEEE Transactions on Power Systems*, 588-589.

Takriti, S., Birge, J. R., & Long, E. (1996). A Stochastic Model for the Unit Commitment Problem. *IEEE Transactions on Power Systems, 11*(3), 1497-1508.

Wilson, R. (2002). Architecture of power markets. *Econometrica, 70*(4), 1299-1340.

Zheng, T., & Litvinov, E. (2008). Contingency-based zonal reserve modeling and pricing in a co-optimized energy and reserve market. *IEEE transactions on Power Systems, 23*(2), 277-286.