2025-940
Market model and analysis, non-convex costs

Åpen informasjon / Public

R&D Project Report

Bid formats reflecting non-convex supply costs give significant efficiency improvements

An analysis based on a simulation of co-optimized electricity and balancing capacity markets

Version: 2026-08-26

Contents

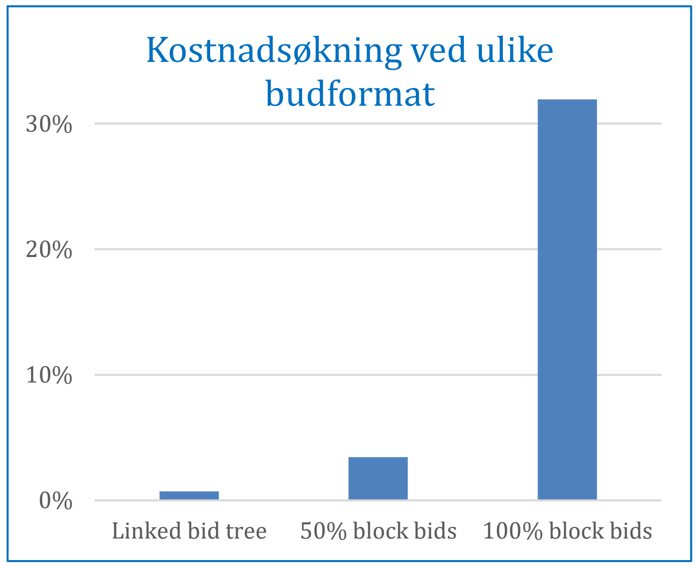
Sammendrag: Budformat er viktigere enn samoptimering

Formål og avgrensning

Denne studien analyserer effekten av budformat på effektiviteten i samoptimert anskaffelse av energi og balansekapasitet dagen før driftstimen, med fokus på ikke-konvekse kostnader. Vi utvikler et modellverktøy inspirert av ACERs 2024-studie "Welfare Benefits of Co-Optimising Energy and Reserves", men bruker stykkevis lineære produksjonskostnader. Inputdataene er realistiske, men representative bare for de valgte scenariene. Studien fokuserer derfor på kvalitative og strukturelle sammenhenger. Budformatene er definert spesifikt for denne studien. Strategisk adferd og markedsmakt omfattes ikke av analysen.

Budformat påvirker effektivitet og omfordeling

Våre resultater viser at upresise budformat, for eksempel blokkbud over flere timer, fører til ineffektiv ressursbruk (økte totalkostnader) på grunn av upresis kostnadsinformasjon og redusert fleksibilitet for markedsalgoritmen. Dette mønsteret gjelder både for samoptimering av energi og balansekapasitet og for rene energimarkeder. De estimerte velferdstapene fra upresise budformat overstiger effektivitetsgevinstene for samoptimering av energi og balansekapasitet som ble estimert i ACERs 2024-studie.



I tillegg til effektivitetstapet har upresise budformat betydelige fordelingsvirkninger. Ineffektiv ressursbruk og høyere totalkostnader fører til høyere gjennomsnittspriser og en omfordeling av velferd fra forbrukere og TSO-er til produsenter. Dette mønsteret varierer mellom scenarier i studien, men det er systematisk.

En ny tilnærming til markedsdesignanalyse

Vår studie viser at en grunnleggende markedsmodell for våre formål kan utvikles med moderat innsats, og dermed gi kunnskap som ikke kan oppnås fra kostnadsbaserte modeller (som gir perfekt kostnadsinformasjon til markedsalgoritmen) eller fra simuleringer som bruker historiske bud (basert på ukjente kostnadsstrukturer). Vår tilnærming er derfor godt egnet for regulatorisk arbeid i tidlig fase, der formålet er å isolere og forstå designvalg og avdekke strukturelle effekter før de blir implementert og satt i drift.

Implikasjoner for politikk og markedsdesign

Våre funn har direkte implikasjoner for prioriteringen av videre markedsutvikling i Europa. Markedsdesign bør utvikles med fokus på en god forståelse av nytte og kostnader. Samoptimering av energi og balansekapasitet vil ikke forsvare anstrengelsen i utvikling, implementering og drift om ikke budformatene utformes slik at kostnadsstrukturene kan representeres godt. Vi mener at kostbare og komplekse markedsutviklingsprosjekter med liten eller tvilsom nytte undergraver legitimiteten og tilliten til europeisk markedsintegrasjon.

Videre arbeid

Vi planlegger å utforske pris- og omfordelingsmekanismer mer i dybden, og utvide modellen til sekvensiell klarering av balansekapasitet og energi.

Statnett

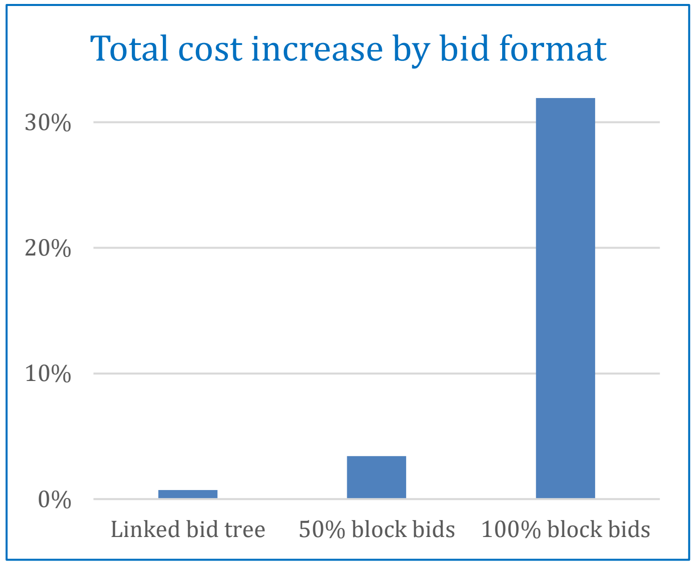
Summary: Bid formats matter more than co-optimization

Purpose and scope

This study analyzes the effect of bid format on efficiency in the co-optimized day-ahead procurement of energy and balancing capacity, with a focus on non-convex costs. We develop a modelling framework inspired by ACER's 2024 study "Welfare Benefits of Co-Optimising Energy and Reserves," using piecewise-linear production costs. The input data are realistic but representative only of the selected scenarios. The study therefore focuses on qualitative insights and structural relationships. Bid format definitions are specific to this study. Strategic behavior and market power are not covered by the analysis.

Bid formats shape efficiency and redistribution

Our results show that inaccurate bid formats such as multi-hour block bids lead to suboptimal dispatch (increased total costs), due to inaccurate cost structures and reduced algorithmic flexibility. This pattern holds both for the joint clearing of energy and balancing capacity markets and for energy-only markets. The estimated welfare losses from bid format restrictions exceed the efficiency gains reported in other studies for the co-optimization of energy and balancing capacity.



Beyond the efficiency loss, imprecise bid formats have significant distributional implications. Inefficient dispatch and higher total costs lead to higher average prices and a redistribution of welfare from consumers and TSOs to producers. The study shows that this pattern varies across scenarios but is systematic.

A new approach for market design analysis

Our study shows that a fundamental market model for our purposes can be developed with moderate effort, providing insight that cannot be obtained from cost-based models (which assume perfect cost information reaches the market algorithm) or from simulations using historical bids (based on unknown cost structures). Our approach is therefore well suited for early-stage regulatory work, where the purpose is to isolate and understand design choices and reveal structural effects before they are implemented and put into operation.

Implications for policy and market design

Our findings have direct implications for the prioritization of further market development in Europe. Market design should be developed with a good understanding of benefits and costs. Co-optimizing energy and balancing capacity will not justify the effort of development, implementation, and operation unless bid formats are designed so that cost structures can be represented properly. We argue that costly and complex market development projects with little or dubious benefit undermine the legitimacy and trust of European market integration.

Future work

We plan to explore pricing and redistribution mechanisms in more depth and extend the model to sequential clearing of balancing capacity and energy.

1 Introduction

1.1 Objectives of the study

The objective of this study is to assess how the quality of input information—specifically the bid format representation of non-convex production costs —affects the performance of market mechanisms, in particular the joint procurement of energy and balancing capacity. The analysis focuses on the role of bid formats in shaping welfare outcomes, prices, and distributional effects, rather than on the design of pricing rules.

The study addresses the following questions:

- **Information on costs:** How do different bid formats succeed or fail in representing the non-convex costs of the power system?
- **Welfare and efficiency:** To what extent does information loss in the bidding process lead to inefficient dispatch and reduced social welfare?
- **Distributional effects:** How does poor bid representation affect prices and the distribution of surplus between consumers and producers?

The present study builds on earlier internal Statnett work conducted following the ACER Co-optimization Benefit Study (2024). Our analysis replicated the core modelling approach under the assumption of perfect cost representation, focusing on the efficiency gains from joint scheduling of energy and balancing capacity. While qualitatively consistent with the ACER results, the estimated efficiency gains were found to be lower and sensitive to modelling assumptions[1]. More importantly, both the ACER study and our subsequent analysis rely on an idealized setting in which the market clearing algorithm has access to complete and accurate cost information. The impact of bid formats was not analyzed. We include a brief summary of this analysis in appendix G.

Our current study focuses on fundamental principles and does not attempt to represent any real world beyond the chosen input data. The input data are nevertheless calibrated to be representative of realistic system conditions, ensuring that the results remain economically interpretable and intuitive.

The study was conducted for Statnett by Optimeering AS with active participation from Statnett.

1.2 Regulatory context

The European market-clearing algorithm (EUPHEMIA) is jointly governed by NEMOs and TSOs under CACM. Any change to market clearing must follow formalized algorithm governance and R&D procedures. The Electricity Balancing Guideline requires the development of methods for efficient allocation of cross-zonal capacity for energy and balancing capacity (henceforth "BC"), either by sequential markets (called "market-based") or co-optimized in one joint market clearing (henceforth "co-opt"). ACER published its Co-optimization Benefit Study in 2024, and subsequently included co-opt R&D in its decision 11/2024 on amendments to the price coupling algorithm.

The R&D following ACER's decision is carried out by NEMOs and TSOs within MCSC. The focus is on feasible design, implementation and operation within current market processes and IT systems. The impact of non-convex costs on bid formats, pricing principles, efficiency and redistribution is largely outside the scope of the work. A gap therefore exists between the feasibility-oriented R&D and analytical work aimed at understanding how bid formats interact with non-convex cost structures.

[1] The total cost saving of co-opt compared to sequential BC and energy markets was 0.97% in ACER's study, and 0.60% in the Statnett study.

1.3 Fundamental questions in market design

A market mechanism can be viewed as a sequence of three distinct tasks: the **collection of information** (cost, benefit, technical characteristics), **welfare-maximizing allocation** through a market algorithm, and the **calculation of market prices**. In a textbook market with convex (and twice differentiable) costs, these tasks are conceptually straightforward and solved with linear programming. However, the presence of non-convexities—such as start-up costs and increasing returns to scale—complicates each step of the sequence.

Academic literature has extensively explored the "downstream" challenges of market design, particularly efficient pricing rules. The quality of the information contained in bids has received far less attention.

The efficiency of any market algorithm is inherently limited by the information it receives, and there is a risk that garbage in leads to garbage out. If the bid formats are not designed to represent the underlying physical cost structures, the resulting allocation may be suboptimal regardless of the sophistication of the algorithm.

When cost structures are non-convex, the fundamental theorems of welfare economics no longer hold. In such environments, a single set of linear clearing prices cannot, in general, ensure both an efficient resource allocation and full cost recovery for all participants.

A robust market design should make it **possible** for participants to represent their fundamental cost structures accurately. However, whether market participants **choose** to represent their fundamental cost structures accurately depends on their individual bidding strategies.

While market behavior is a critical factor in real-world outcomes, this study does not model strategic bidding or exercise of market power. In a regulatory framework, strategic behavior is addressed through **market monitoring**, which serves as a necessary complement to the structural choices of market design. Our analysis is limited to the technical and economic performance of the market mechanism itself. It assumes that bids are intended to reflect actual production costs within the constraints of the provided formats, to isolate the impact of the design itself.

1.4 Report structure

Objectives and context are presented earlier in this chapter. Chapter 2 presents market design challenges with non-convex costs. Chapter 3 describes our simulation model and discusses key design choices. Chapter 4 presents our analysis, and chapter 5 concludes this report. The appendices offer more information on our model and the data used for the analysis.

2 Market design challenges with non-convex costs

2.1 The departure from textbook microeconomics

In textbook microeconomics, the fundamental theorems of welfare economics (FWT1, FWT2) provide a powerful link between social welfare and market outcomes. Under the assumption of convexity, FWT1 states that any competitive equilibrium is Pareto optimal, while FWT2 implies that a social planner's optimum can be achieved through decentralized market clearing. In such "well-behaved" environments, market clearing is a linear programming (LP) problem where shadow prices perfectly clear the market, ensuring both social efficiency and full cost recovery for all participants.

While both theorems share assumptions such as perfect information and the absence of externalities, their requirements regarding the structure of production differ significantly. FWT1 primarily assumes price-taking behavior and suggests that a market equilibrium, if it exists, is Pareto optimal. FWT2, however, is more demanding as it assumes convexity of both production and preference sets. Without convexity, the price mechanism cannot guarantee that a socially desired optimal allocation can be decentralized.

Power systems fundamentally violate these assumptions, due to non-convexities of three types:

- **Start-up costs:** Fixed costs incurred to bring a unit online, regardless of the subsequent production level. These costs may vary (e.g., warm vs. cold start-up) but remain indivisible.
- **Minimum load constraints:** Technical requirements that prevent units from operating below a certain threshold, creating a "hole" in the **feasible set** seen by the market algorithm.
- **Increasing Returns to Scale (IRS):** Decreasing average variable costs AVC(P) as output P increases, meaning marginal cost pricing alone fails to cover total costs.

The non-convexities are even more prominent in the provision of **Balancing Capacity (BC)**, involving energy suppliers near the energy market clearing where the BC opportunity cost is lowest:

- **Inframarginal** energy market suppliers (marginal energy cost below the market price)**:** BC provision requires operation at a sub-optimal energy point (e.g., part-load), resulting in higher average energy costs.
- **Extramarginal** energy market suppliers (marginal energy cost above the market price)**:** BC provision also requires starting "out-of-the-money" units where the energy price does not cover the energy costs. By running at minimum load at an indivisible cost (at a negative energy market profit), an asset can provide BC for up regulation at zero marginal cost.

The fundamental challenge is that a single set of linear clearing prices that ensures both efficient allocation and cost recovery may not exist. In *Linear prices for non-convex electricity markets: models and algorithms*, Van Vyve (2011) points out that strict linear pricing in non-convex markets is a mathematical impossibility, consistent with earlier work by Gomory and Baumol (1960), Scarf (1986) and others. Consequently, market clearing is no longer a simple intersection of marginal cost and utility curves, but a complex combinatorial optimization task—akin to a **"Knapsack Problem"**. Categorized as **NP-hard**, the complexity of such problems means that as the number of discrete choices (binary variables for start-up/shut-down) increases, the computational effort required to find an optimal solution grows exponentially. For large-scale power systems, this makes the search for an optimal dispatch a significant computational challenge.

The fundamental challenges of non-convexities challenge every stage of the market process. In the following section, we explore how non-convexities challenge all three distinct tasks of a market mechanism: **information collection, maximization of welfare**, and **price calculation**.

2.2 The three tasks of the market mechanism

Step 1: Collection of information on costs and utility

The first task of any market mechanism is to collect the necessary data on costs, benefits and constraints needed to perform an efficient allocation of resources. This includes market bids and trading capacities. Ideally, the information in bids should reflect the true underlying cost structure of the participants. However, in European power markets, bid formats are a patchwork of evolutionary leftovers that do not reflect the fundamental cost structures.

There is a tradeoff between bid format simplicity and good representation of real costs. Linear "price-quantity" pairs cannot communicate the non-convex cost structures. Block bids (spanning several market time units while offering all or none) is one way of ensuring start cost coverage in the European power market. While they reduce risk for participants by ensuring a "fixed volume or nothing" outcome, they act as a black box for the market algorithm. They effectively hide the underlying cost structure — such as start-up costs and minimum load constraints — behind a single lump-sum price, and they reduce the flexibility of the market algorithm to decide the output level and duration of the offered energy.

Linked bids (using parent-child and other bid relations) may better represent fundamental cost structures if they are well designed, but they require more efforts from the bidder.

Multipart bids may be designed to describe cost structures and technical constraints in detail. The bid formats of US power markets go some way in this direction, including start costs, ramp rates, decreasing average costs, minimum down times and more in the day-ahead market clearing or SCUC (Security Constrained Unit Commitment). We discuss bid formats in chapter 3.4

Step 2: Welfare maximization

Once the bids are collected, the second task is to select the set of bids that maximizes total social welfare while satisfying demand and other constraints. In an imaginary world where costs are convex, there is a perfect strong duality between the allocation (the primal) and the prices (the dual). The optimization is a straightforward operation for an LP algorithm. Every constraint has a shadow price that tells us exactly what that resource is worth on the margin.

With the presence of non-convex costs, the dual relationship of constraints and shadow prices breaks down. There are no longer shadow prices that can clear the market and ensure cost recovery for all participants. The approach shifts from simple **linear programming (LP)** to **Mixed-Integer Linear Programming (MILP)**. With our non-convexities - start-up costs, minimum load restrictions and increasing returns to scale - the algorithm must make binary, discrete decisions: to start a unit or not, to accept a block or reject it. The task becomes combinatorial and similar to a **Knapsack problem**. In a large-scale optimization, the algorithm must find a feasible solution that is "good enough" within strict time limits, as finding the absolute global optimum can be computationally prohibitive.

The information on costs and utility contained in market bids may or may not be accurate. If the input data is inaccurate, the resource allocation is still a complex task. It may still be NP-hard, but to little benefit.

Step 3: Price Calculation

The final task of the market mechanism is to determine the market prices for financial settlement. In a convex world, prices are a byproduct of the optimization. In our non-convex reality, however, the prices are no longer natural phenomena to be discovered, but created or chosen by humans based on desired properties of market prices. Such properties could be:

- Efficient market clearing (it is a desired property, but unfortunately not on the menu)
- Uniformity
- Marginal
- Minimizing the amount of skipped bids that are in the money ("PRB" in SDAC speech)
- Ensuring cost recovery
- Reducing missing money and the need for make-whole payments
- Easily calculated.

Because linear prices ("price per unit") cannot satisfy all ideal economic conditions simultaneously in a non-convex market, we face a difficult choice. We can have prices that reflect marginal costs, but then some generators will not cover their start-up costs. Or we can inflate prices to ensure cost recovery, but then we lose the "marginal" signal for consumers and producers alike. If we opt for uniform (or near-uniform) prices, we must choose our pains, either suffering skipping bids that are in the money, or the need for make-whole payments or uplifts (leaving us at near-uniform prices).

The quest for good pricing principles should not aim at finding "the right prices", as they do not exist. Instead, we need to find "good enough prices", with deficiencies that are known and preferred to the alternatives. Academic literature, in particular in the US, has focused on finding the best trade-off between the desired pricing properties, while paying little interest to the input data that the welfare maximization and the price calculations are built on. Whatever pricing principles we choose, they do not directly influence the efficiency of the market results, i.e. the welfare maximization. That is taken care of by the input data accuracy and the market algorithm.

The next chapter describes our simulation model and the design choices made in order to handle the challenges described above.

3 Methodology: The Simulation Model

3.1 Model overview

We have developed a model considering different purposes, such as:

- Analysis of the impact of bid formats/input data quality in markets
    - Energy markets
    - BC markets
    - Co-optimized BC and energy markets, facilitate choices like
        - Co-opt or not? (Comparison to alternatives)
        - Good co-opt or bad co-opt? (Analysis of market design choices)
    - Algorithm performance
- Analysis of co-optimization efficiency gains
    - Separate gains from efficient BC procurement and from BC exchange.

The modeling framework for this study is inspired by ACER's Co-optimization Benefit Study (2024), which analyzes the efficiency of clearing BC and energy market sequentially or jointly, using a fundamental model of the production system, and generously giving the market algorithm perfect information on energy production cost structures. We add a step of markets bids between the cost data and the algorithm in order to study the impact of input data quality (bid formats) on market efficiency. We also improve the generator cost model to capture IRS in a more general way than a mere constant marginal cost from minimum to maximum output levels.

Our model shares the following characteristics with the ACER study:

- Time horizon day-ahead from midnight to midnight.
- Several hundred power generating units, modelled individually based on a range of generation technologies.
- Fuel costs defined for the included technologies.
- A dozen or so bidding zones, connected by trading capacity.
- Eight days representing a year: workday and weekend for each of the four seasons.
- Cost-based bidding (no analysis of bidding behavior or strategy, though this could be done by manual bid preparation).
- Inelastic demand defined by time series.
- Wind and solar power generation defined in time series.

Our model differs from the ACER study in these respects:

- 60 minutes market time resolution (MTU)
- ATC approach for trading capacity instead of flow-based capacity allocation

3.2 Data overview

3.2.1 Market areas and trading capacities

The model uses a dozen or so European bidding zones similarly to the ACER Co-optimization Benefit Study, and trading capacities on ATC type between these bidding zones. The model is configurable, and the bidding zones can be included or excluded on individual basis. Figure 1 shows the areas used in our analysis together with ATC example values. The colors define regions for the comparison of market-wide and regional exchange of balancing capacity described in chapter 4.4

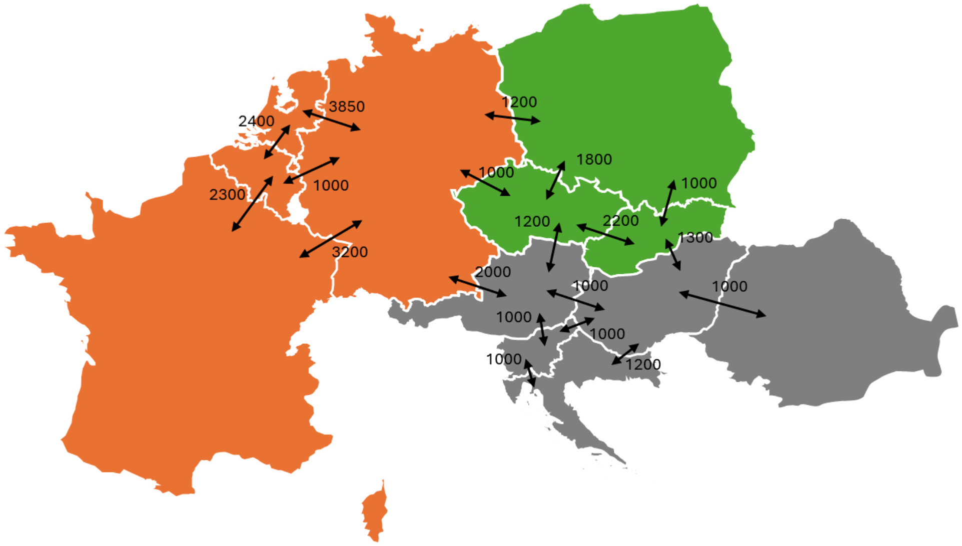


Figure 1 Market areas

3.2.2 Cross-zonal capacity used for BC

The trading capacities (cross-zonal capacities, or CZC) available for BC exchange can be defined as a fraction of the total available transfer capacity (ATC). This fraction can be set to zero in order to study the efficiency of co-optimized energy and balancing capacity markets without cross-zonal exchange of balancing capacity. Setting this fraction to zero for selected borders can also be used to assess the benefits of regional BC exchange relative to market-wide exchange.

In the model, the CZC allocated to BC exchange corresponds directly to the exchanged BC capacity. In other words, 1 MW of BC exchange across a border displaces 1 MW of energy trade across the same border, provided that the same directional CZC is used. This assumption may appear conservative, since the actual activation of balancing energy will often require less transmission capacity. A more efficient allocation of CZC to BC exchange could potentially be achieved by accounting for the joint probability distribution of balancing energy activations across areas. While this is an interesting topic, it is beyond the scope of the present study.

3.2.3 Generation mix

The production system initially consists of 3-400 generating units of different types. For each bidding zone, the generating units reflect a generation mix similar to the one used in the ACER Co-optimization Benefit Study, which was based on installed capacities of 2023 according to ENTSO-E data. We emphasize that our study focuses on principles, and the calibration of the generation mix or other input data are not critical to the analysis.

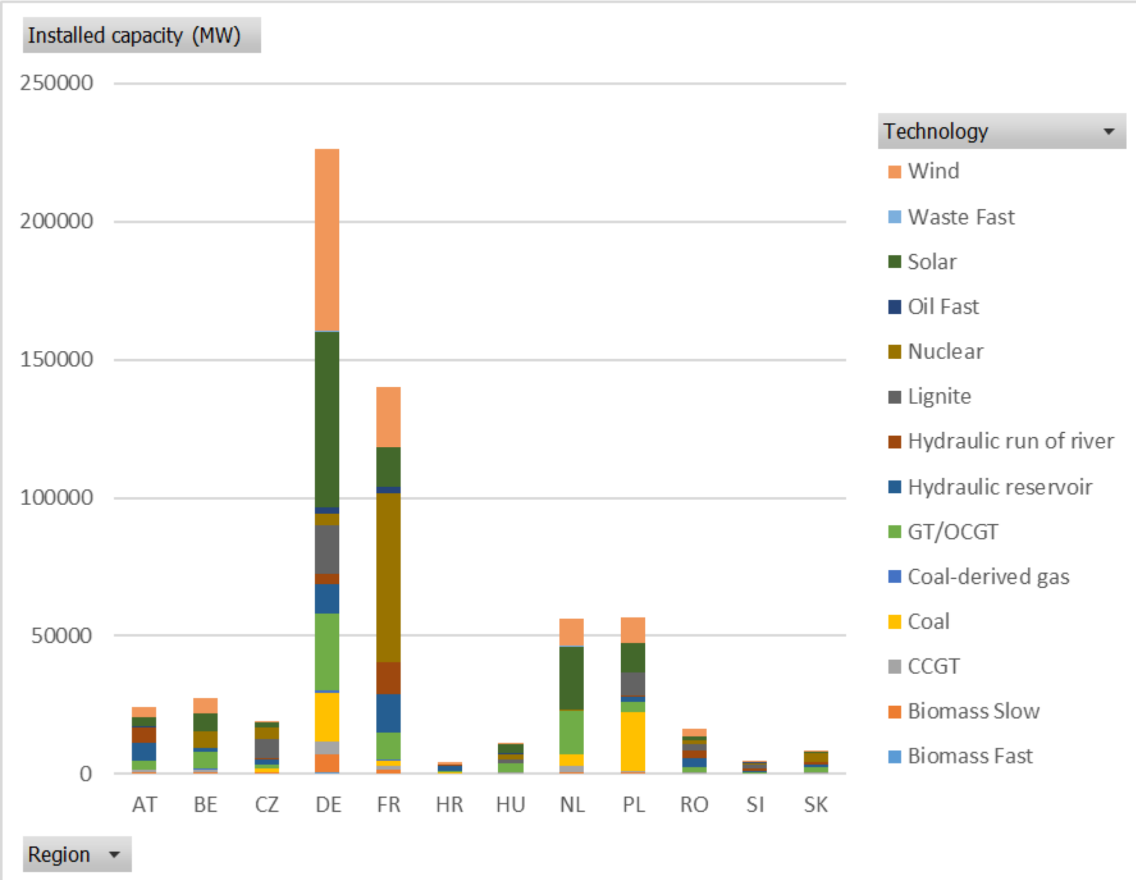


Figure 2 Generation mix

3.2.4 Conventional generation technologies

Parameters of thermal generation technologies and fuel costs are included in appendix C. One set of parameters is used in our analysis – we have not studied fuel or emission costs sensitivities.

Parameters of hydropower generation technologies and water values are also included in appendix C. The water values vary between seasons in our study in order to reflect the impact of different reservoir states on the energy supply costs.

As our study focuses on principles, the calibration of input data such as generation cost parameters is not critical to the analysis.

3.2.5 Intermittent generation profiles

The model uses time series per bidding zone to represent wind power and solar power generation for two days of spring, two days of summer, two days of autumn and two days of winter. In each season, the two demand profiles aim to represent workday and weekends. We emphasize again that the calibration of input data is not critical to the analysis.

The model also uses time series to represent run-of-river hydro generation by season.

3.2.6 Storage units

Not implemented.

3.2.7 Energy demand

The model uses time series per bidding zone to represent energy demand per bidding zone and market time unit.

3.2.8 BC demand

The balancing capacity demand defined per bidding zone is constant for regulation in each direction (up/down). The values are consistent with those used in ACER's Co-optimization Benefit Study, though this is not critical to the analysis.

3.3 Generation cost structures

3.3.1 Conventional technologies

We consider "conventional" any generation unit that has a constant output capacity and a constant energy cost for the time horizon of the market clearing. For our analysis, this means thermal and hydropower generation.

Energy dispatch costs:

We represent the energy costs by a piecewise linear (PWL) average cost function AVC(P) between the minimum output level Pmin and the maximum level Pmax. Thermal generation units are assumed to have their lowest AVC(P) at Pmax, whereas hydropower units have their lowest AVC(P) at some P below Pmax. The figure below shows the modelled cost structure of a hydropower unit.

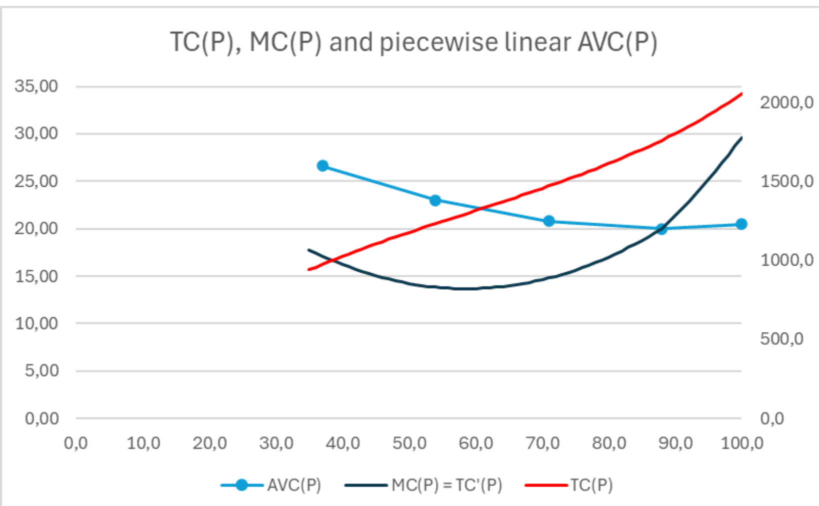


Figure 3 Generation cost structure, hydropower

In our analysis, we have defined generating units individually using four or fewer linear segments for thermal units, and five or fewer linear segments for hydropower units. We have defined the AVC(P) as a PWL curve as to emulate the following properties:

- AVC(P) > 0; AVC'(P) < 0; AVC''(P) > 0 for Pmin < P < Pbest
- AVC(P) > 0; AVC'(P) > 0; AVC''(P) > 0 for Pbest < P < Pmax

These costs are non-convex due to the minimum load restriction Pmin > 0, and due to the decreasing AVC(P) for Pmin < P < Pbest, i.e. increasing returns to scale (IRS).

> *Note that our generation cost model above differs from the one used in the ACER Co-optimization Benefit Study, which is a linearization of total costs:*
>
> - *TC(P) = K + MC*P, P > Pmin*
>
> *That model also represents non-convexities from minimum load constraints and increasing average costs. The main difference from our cost model is that the marginal cost is constant on the entire range from Pmin to Pmax, whereas our model has marginal cost on each PWL segment. We see two disadvantages in the model used by ACER's study:*

- *Marginal costs and average costs do not converge around the level of lowest AVC. The gap between marginal and average costs near optimal generation complicates pricing.*
- *The constant marginal cost implies constant opportunity costs for BC, and once a generating unit is chosen for BC provision, all flexibility is used for BC. This simplifies the calculation for the algorithm, but it might not offer the desired insights from the analysis.*

Start costs:

We use costs per MW installed capacity, representing two types of start costs:

- Energy (heat) loss per startup, for thermal units.
- Impact of one startup on the maintenance cycle, for all conventional units.

We do not distinguish between cold and warm startups.

3.3.2 Intermittent generation

For run-of-river hydropower, wind and solar generation, we use the same fundamental cost structure as for conventional technologies with the following adjustments:

- Pmin = 0
- AVC(P) = 0
- The maximum output is defined by timeseries that represent seasons and weather in a deterministic way.
- Start costs are not considered.

3.3.3 Storage units

Not implemented.

3.4 Bid formats and bid generation

3.4.1 Bid formats included

The aim of our study is to add a layer of bid formats between the real world (defined by the generation cost model) and the market algorithm in a model similar to that of ACER's Co-optimization Benefit Study.

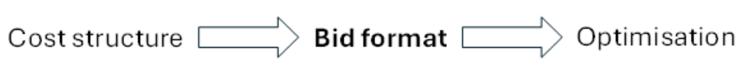


Figure 4 Cost data processing

This enables us to study the impact of information quality on the market mechanism and the market outcome. We chose three different bid formats for this layer:

A. Raw data or "combined bids"
    - The combined bids serve two purposes:
        - They represent the actual generation costs. As far as the model is concerned, they do not approximate the costs – they define the costs.
        - They serve as a format of information on costs to the market algorithm. Conceptually, they do the same task as the cost data in ACER's Co-optimization Benefit Study.
    - "Combined" refers to the combined offer of energy and balancing capacity in one bid format.
    - We use piecewise linear average costs as described in section 3.3.1.

B. Linked trees
    - This is an attempt to approximate the actual generation cost structure using simple bid elements in a not-so-simple structure.
    - The bid structure can be designed to achieve any level of accuracy by increasing the number of segments in the (PWL) average cost model.

   - The bid structure can easily be produced by a few lines of Python code. The apparent complexity is therefore no obstacle for implementation.

C. Block Bids
   - We need to compare the bid formats above with formats that are less inspired by fundamental cost structures and more by markets in the real world. A block bid format for our purposes might be designed in different ways, and some might be more relevant than others. We consider the following features important for energy block bids:
     - Information quality: A lump-sum price of the energy block hides the cost structure (i.e. the start cost, the minimum load and the decreasing AVC(P)) from the algorithm.
     - Flexibility: A block duration reduces the flexibility of the algorithm to choose the hours of delivery from an asset. The flexibility may be further reduced by constant power output for the duration of the block.

Our model can use bid formats B and C in combination, i.e. block bids for some generating units and linked bid trees for other generating units in the same market optimization.

3.4.2 Conventional technologies

3.4.2.1 Combined bids = real costs, basic asset data

The real generation costs and constraints are defined by a basic asset data table containing the following properties:

- An identifier.
- Minimum output level, Pmin.
- Maximum output level, Pmax (installed capacity).
- Start costs per generating unit.
- Average cost of energy AVC(P) from Pmin to Pmax defined as a PWL function.
- Capability of delivering BC for up regulation.
- Capability of delivering BC for down regulation.
- "BC Premium" used as a minimum profit for BC capacity per MW.
  - One might argue that the only BC cost is opportunity cost, or one might disagree, in which case a "price" of BC may be defined here. This is not used in our initial analysis.

Bid generation

No bid preparation is done for the "combined bids" – the raw data are served to the algorithm in its pure form.

3.4.2.2 Linked bid trees

The linked bid trees are structured as follows:

- SC: A parent bid without MTU reference for the start cost. This element serves as an intertemporal link in order to account for one startup per uninterrupted operation period.
- ML (child of SC): An indivisible energy quantity offered per MTU.
  - Quantity: Pmin (or some other power output > Pmin).
  - Price: AVC(Pmin) or AVC(some P > Pmin).
- IE (child of ML or of an IE): divisible energy quantity offered per MTU.
  - Quantity: A segment (in MW) of the PWL generation cost.
  - Price: Total cost increase over the cost segment divided by the quantity.
- BC_down (child of an IE)
  - Quantity: Flexible capacity (P - Pmin) from the last selected energy bid in a chain of energy bids, or a maximum BC_down if defined in the basic asset data.
  - Price: Zero or a "premium" (not used in our study).
- BC_up (child of ML or of an IE)
  - Flexible capacity (Pmax - P) from the last selected energy bid in a chain of energy bids, or a maximum BC_up if defined in the basic asset data.

Note that the indivisible ML and the divisible IE bids form a chain of parent-child bids, and the attached BC_down and BC_up bids form branches from the stem of energy bids.

Algorithm assumptions:

- SC: The market algorithm adds the SC to the total energy costs when the bidding asset goes from unchosen in one MTU to chosen in the next.
- Parent-child bids: A parent must be accepted 100% before a child bid can be selected.
- BC bids can only be chosen from the last accepted energy bid.
    - The partial selection of a marginal energy bid might deserve special treatment, but we consider the impact negligible, and leave it undone

Bid generation

The basic asset data is fed into a script that generates an excel file containing the linked tree bid structure. The file may look like Table 3-1 below. The colors match those of the described bid elements above.

Bid_ID	Parent_Bid_ID	Excl_Bid_ID	Bid_Type	Asset	Area	MTU	Quantity	Price
G12_SC			SC	G12	Dummy		1	1000
G12_ML_01	G12_SC		ML	G12	Dummy	1	49,37	26,58
G12_AL1_01	G12_ML_01		IE	G12	Dummy	1	16,10	2,26
G12_AL2_01	G12_AL1_01		IE	G12	Dummy	1	16,10	8,48
G12_AL3_01	G12_AL2_01		IE	G12	Dummy	1	16,10	10,95
G12_AL4_01	G12_AL3_01		IE	G12	Dummy	1	16,10	14,19
G12_AL1_01_BC_DOWN	G12_AL1_01		BC_DOWN	G12	Dummy	1	16,10	
G12_AL2_01_BC_DOWN	G12_AL2_01		BC_DOWN	G12	Dummy	1	32,19	
G12_AL3_01_BC_DOWN	G12_AL3_01		BC_DOWN	G12	Dummy	1	45,50	
G12_AL4_01_BC_DOWN	G12_AL4_01		BC_DOWN	G12	Dummy	1	45,50	
G12_ML_01_BC_UP	G12_ML_01		BC_UP	G12	Dummy	1	45,50	
G12_AL1_01_BC_UP	G12_AL1_01		BC_UP	G12	Dummy	1	45,50	
G12_AL2_01_BC_UP	G12_AL2_01		BC_UP	G12	Dummy	1	32,19	
G12_AL3_01_BC_UP	G12_AL3_01		BC_UP	G12	Dummy	1	16,10	
G12_ML_02	G12_SC		ML	G12	Dummy	2	49,37	26,58
G12_AL1_02	G12_ML_02		IE	G12	Dummy	2	16,10	2,26
G12_AL2_02	G12_AL1_02		IE	G12	Dummy	2	16,10	8,48
G12_AL3_02	G12_AL2_02		IE	G12	Dummy	2	16,10	10,95
G12_AL4_02	G12_AL3_02		IE	G12	Dummy	2	16,10	14,19
G12_AL1_02_BC_DOWN	G12_AL1_02		BC_DOWN	G12	Dummy	2	16,10	
G12_AL2_02_BC_DOWN	G12_AL2_02		BC_DOWN	G12	Dummy	2	32,19	

Table 3-1 Linked bids

3.4.2.3 Block bids

Inspired by fill-and-kill block orders in the SDAC algorithm, we design a "block order" for a fixed quantity and duration combined with child bids per MTU offering BC down and either energy or BC up. This is shown in Figure 5 below.

- Energy block bid, fixed quantity and duration over several MTUs – accept all or none:
    - Quantity: We choose "Pmax minus the last energy cost segment defined in the basic asset data". This leaves some flexibility for offering BC_up, while offering energy at a part-load level where the energy unit cost AVC(P) is not drastically higher than at Pbest (i.e. at Pmax).
    - Price: AVC(P) at the output level defined by the chosen quantity.
- Energy child bid per MTU

    - Quantity: Equal to the last energy segment defined in the basic asset data, i.e. the remaining generation capacity.
    - Price: Identical to the price in the block. Not because it is "reasonable", but because non-decreasing bid prices is the established practice in the European power market. A cost-based price would be slightly lower.
    - Exclusive link to the "sister bid" for BC_up. Both bids cannot be accepted.
- BC_down:
    - Quantity: Flexible capacity (P - Pmin) from the block bid quantity, or a maximum BC_down if defined in the basic asset data.
    - Price: Zero. Use of "BC premium" is not supported for block bids in our model.
- BC_up quantity:
    - Quantity: Equal to the last energy segment defined in the basic asset data.
    - Price: Zero. Use of "BC premium" is not supported for block bids in our model.
    - Exclusive link to the "brother bid" for energy. Both bids cannot be accepted.

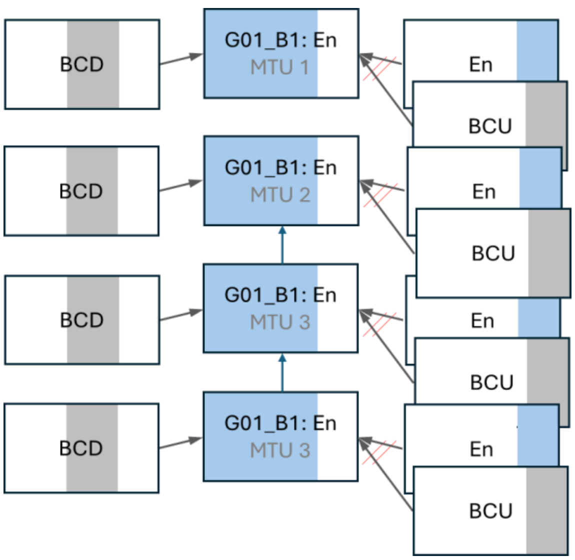


Figure 5 Block bid structure

Our block bid format satisfies three basic wishes:

- It is easy to build.
- It represents fundamental costs and technical capabilities less accurately than the combined bids and linked parent-child bids above, thus allowing us to study the impact of bid formats blurring the cost information received by the market algorithm.
- It reduces the algorithmic flexibility. Yet it includes considerable flexibility for the market algorithm to use for energy and BC purposes.

Bid generation

As for linked tree bids, a script generates the block bid structure in Excel format.

3.4.3 Bid formats and bid generation for intermittent generation

Differences from conventional technologies are summarized below.

- Combined bids = real costs, basic asset data
    - Same format as for conventional technologies, but the quantity is limited by the time series for run-of-river hydro, wind power and solar power.
- Linked bid trees
    - Same format as for conventional technologies, but the quantity is limited by the time series for run-of-river hydro, wind power and solar power.
- Block bids

- Block bids are not used for intermittent renewable generation.

3.4.4 Bid formats and bid generation, storage units

Not implemented.

3.4.5 Portfolio bidding

We have not designed any bid format for portfolios of different or similar generation units. It is hard to see that this can be done well. However, our model can be used for incorporation of manually prepared portfolio bids using the bid formats that are implemented. One purpose of this could be to study the benefit of leaving the portfolio optimization to the market algorithm.

3.5 Welfare maximization

The algorithm is implemented in Python and proceeds through a sequence of steps, as illustrated in the flow chart below. Many of the steps involve separate optimization models that are all written using the Pyomo framework. The primary inputs (described in the preceding section) are supplemented by user-defined settings provided either through configuration files or directly as model arguments. These settings control the path the model takes (strategy), filter the input data accordingly and set important model parameters (share of total trade capacity to be used for BC markets, local balancing procurement limits, etc.). For example, the user selects a season and day type, which determines which demand profiles, water values and intermittent generation profiles are applied in the run. Each simulation covers a single day (24 hours), but the algorithm is designed to execute iteratively across multiple seasons and day types, making it straightforward to build a full annual picture by running the model sequentially over different scenario combinations.

3.5.1 The two main optimization models

The market clearing is built around two main optimization models: a mixed-integer unit commitment model, developed drawing on the modelling approaches used in the ACER co-optimization study, and a mixed-integer bid selector model.

Unit commitment model (UC).

> The UC model represents the system at the level of individual generators. Each generator can participate in the energy market, the balancing capacity markets, or both, depending on user configuration. The technical relationship between energy production and balancing capacity reservation, such as the constraint that a generator cannot simultaneously produce at maximum output and offer upward BC, is encoded directly through generator-level constraints. The variable cost structure is represented as a piecewise-linear curve, mapping generation output at a set of breakpoints to the corresponding average variable cost, as described in the preceding sections.

Bid selector model (BS).

> The BS model represents the system at the level of individual bids. Each generator is associated with a set of bids per hour and per product, linked together through a hierarchical parent-child structure that reflects the generator's operating constraints: a child bid can only be accepted if its parent bid is also accepted. Bids covering multiple hours can additionally be linked as blocks, requiring joint acceptance or rejection across all hours in the block. Where two bids are technically incompatible, they are placed in a mutually exclusive group, ensuring that at most one of the pair can be selected.

Both models minimize total system procurement cost, comprising startup and fuel costs, subject to demand constraints and market rules. They differ in how generator flexibility is represented, the UC model encodes it through physical constraints on continuous variables, while the BS model encodes it through the bid structure and acceptance rules. The two models share the same treatment of cross-zone capacity, demand balance requirements, local sourcing rules, and penalty costs for unserved demand.

3.5.2 Algorithm design and flow

When the user runs the algorithm, it follows the sequence from input to output described in the flow chart below.

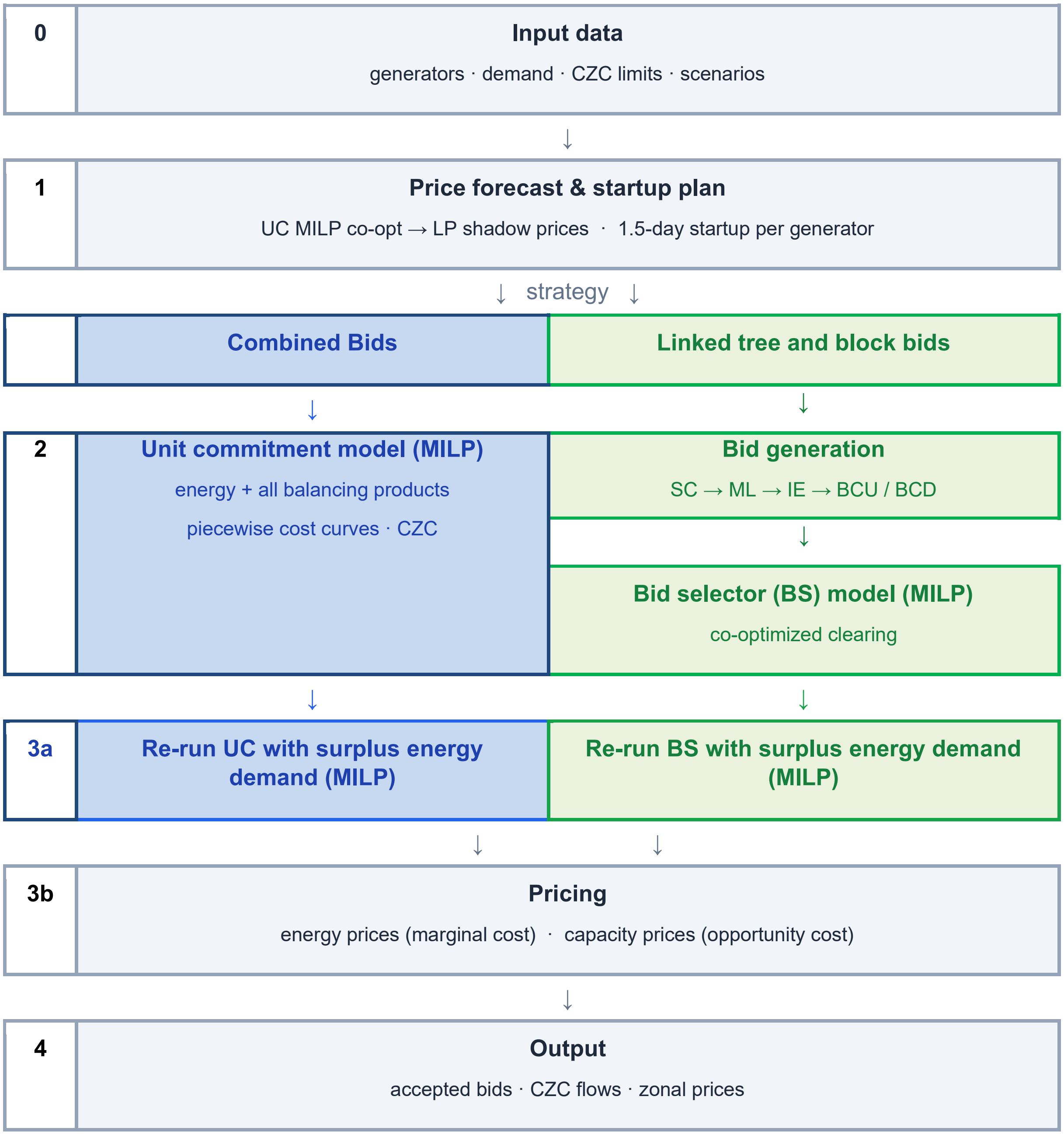


Figure 6 – Algorithm workflow

Step 1 Price forecast and start-up plan

The first step of any simulation run is to establish a day-ahead energy price forecast (for each region and hour) and, from that, a startup plan for each generator. The price forecast is produced by the unit commitment model that co-optimizes energy and balancing capacity in two stages:

- In the first stage, the full mixed-integer problem is solved to determine the optimal commitment and dispatch.
- In the second stage, the binary commitment variables are fixed to the solution from the first stage and the problem is re-solved as a linear program.

The shadow prices on the energy demand constraints from this LP relaxation serve as the price forecast for the startup-plan optimization (below). Beyond being used as input to the start-up plan optimizer, the price forecast is also used for some of the strategies to derive alternative cost estimates for balancing capacity bids, reflecting the opportunity cost of reserving capacity rather than offering it as energy.

The startup plan determines, for each generator, whether it is assumed to begin the day already running. This is established by solving a profit-maximization problem for each generator individually over a 36-hour horizon, using the price forecast as input and the UC model as model structure. The additional 12 hours beyond the 24-hour day are populated by repeating the prices and profiles from hours 1 to 12, giving the optimizer visibility of what follows the planning day and preventing artificial end-of-horizon effects. The key output is whether each generator would start in hour 25 of that extended horizon, which corresponds to the beginning of the day when the same logic is applied to the preceding day. This determines whether a generation unit is considered already running before clearing the market.

While this step logically belongs to bid preparation, it has been implemented within the market algorithm for convenience and as a temporary measure, allowing the present study to focus on other aspects of the analysis.

Step 2 Market clearing

In the second step, the model follows one of two strategies (using one or the other of the main models UC/BS described above) depending on the user's selection.

Combined Bids.

> In this mode, the UC model is set up and solved for the energy and balancing capacity markets jointly. Generators submit a single combined bid that participates across both markets simultaneously, with model constraints governing how capacity is allocated between energy production and BC provision.
>
> The key features are a piecewise-linear cost structure reflecting the generator's variable cost curve, minimum and maximum production limits, startup and shutdown logic, and the direct trade-off between energy dispatch and balancing capacity reservation.
>
> The model finds the commitment and dispatch schedule that minimizes total system cost across all products and hours.

Bid Selector (Linked/Block Bids).

> In this mode, a bid generator module creates explicit bids for each generator based on its technical parameters and fuel costs, following the logic described in section 3.4 . Bids are structured either as linked trees or as blocks.
>
> In the linked tree structure, a startup cost bid sits at the root. Below it, an indivisible minimum-load bid represents the volume the unit must produce whenever it is running. Above minimum load, a chain of divisible energy bids covers incremental output along the generator's piecewise-linear cost curve. From the top of the energy chain, upward and downward balancing capacity bids are attached, reflecting the headroom and reduction margin available at the generator's current dispatch level. This structure encodes the physical coupling between energy and BC within the bid itself.
>
> The market-clearing step then uses the BS mode and selects the combination of bids that satisfies energy and balancing demand at minimum cost, subject to a set of bid constraints. These include a parent-child rule (a child bid can only be selected if its parent is accepted), a leaf rule for balancing capacity bids (capacity can only be offered from the outermost selected energy bid, not from minimum load), an exclusivity rule (at most one of a mutually exclusive pair may be selected), and a block rule (all bids within a block must be accepted or rejected together).

For each price zone and hour, both strategies enforce separate demand targets for energy and each BC product. A local BC sourcing requirement ensures that a minimum fraction of the balancing capacity in each zone is met by local generation rather than imports. Cross-zone capacity (CZC) limits constrain trade of energy and BC between zones to the available interconnector capacity, as well as a separate limit on trade of BC to a percentage (set by the user) of the total capacity. For both strategies/paths, the clearing minimizes total procurement cost across all products, zones, and hours simultaneously. Where demand cannot be fully met, an extremely high penalty value is applied to any shortfall, making unserved demand a last resort rather than an optimized outcome.

The remaining steps (3 and 4) in the flow chart concern the derivation of market-clearing prices which is covered in the following section.

3.6 Price calculation

In our study, the focus is on market efficiency and its dependence on the bid formats. For our purposes we need only a simple price algorithm in order to study redistribution impact due to price movements caused by the bid formats. This may well be done without fine-tuning the pricing principles.

3.6.1 Energy prices

Once the dispatch is determined by the market clearing, energy prices are calculated by a separate pricing model applied to the dispatch. This pricing model considers energy demand only, defined by the energy demand time series plus a share of the BC upward requirement (half of the upward BC requirement is used in our initial analysis). The purpose of this is to get balancing capacity delivered by a mix of inframarginal and extramarginal energy providers. The energy prices serve as references for BC opportunity costs and BC pricing.

Given the reference demand described above, the price in each zone and hour is found as the lowest zonal price that ensures every dispatched generator can at least recover its marginal cost, including a share of its startup cost amortized over the consecutive hours it runs. The minimization pressure pushes prices down until the most expensive committed generator in each zone is exactly in the money: it covers its costs but earns no rent beyond them. Less expensive generators earn inframarginal rents at that price, consistent with standard merit-order pricing.

Price spreading across borders: When energy flows across an interconnector between two zones, the importing zone's price is constrained to be at least as high as the exporting zone's price. This is the standard convergence condition of coupled day-ahead markets: energy flows from lower-priced to higher-priced zones and prices converge whenever the interconnector is not congested.

3.6.2 Balancing capacity prices

The model uses marginal opportunity costs for calculation of market prices for balancing capacity. This is done as described below after the welfare maximizing bid selection is done by the market algorithm:

- Energy market prices are calculated as described in 3.6.1.
- Using these prices and the bid selection from the market algorithm, the actual energy market profit is calculated for each generating unit.
- For each generating unit offering BC, a counterfactual schedule is optimized for the energy market only, and the resulting counterfactual energy market profit is calculated per MTU, or per block for block bids.
- For each MTU, the balancing capacity price in each direction (up/down) is set to the largest difference between actual and counterfactual profit across all generating units — this is the payment needed to compensate the marginal unit for the schedule change required to deliver balancing capacity.

This procedure ensures that necessary "make-whole" amounts are paid to marginal BC providers, and profits to the others. This relies on the view that there is no perfect pricing of energy, but an energy price - whichever it is - is needed for the calculation of BC prices and to ensure that market participants are happy with the market outcome.

Pricing rules across borders:

- Prices spread with trade: price (import) >= price (export)
- Prices on each side of an "uncongested" border (i.e. when trade is not limited by the CZC) should be equal.

It should not be expected that convergence of energy prices across borders implies convergence of balancing capacity prices. While energy prices are largely linked to market balance and cross-zonal trade, BC prices depend on non-convex bid selection and opportunity costs. BC price differences are very blunt measures of the value of cross-zonal capacity used for BC exchange. Further, market prices in the presence of non-convex costs depend on pricing principles chosen, and the choices may differ on different sides of borders for some or all products exchanged.

3.7 Welfare assessment

3.7.1 Total costs

After the welfare-maximization is done by the market algorithm, the dispatch schedules (quantities per MTU for each generation unit) are mapped on the "real cost" data described in chapter 3.4 , i.e. the "combined bids" defining the properties of the generation units. When the market algorithm receives market bids on other formats, the costs are imperfectly represented, and the dispatch is suboptimal. The total energy cost of any market dispatch is compared to that of an optimal dispatch based on perfect information on costs, thus enabling us to determine the impact of the bid formats on the market dispatch efficiency.

3.7.2 Distributional impact

The distributional impacts include producer surplus based on energy and BC revenues, energy consumer surplus (or costs) and TSO surplus (or BC costs) including settlement of BC exchange. All of these depend on chosen pricing rules, and interpretation must be done with care.

4 Results and analysis

4.1 Experimental Setup and Scenarios

We study the modeled market outcomes using scenarios that combine the fundamental data on demand and supply with different bid formats. The demand side features time series of inelastic energy demand covering business days and weekends across four seasons per MTU for all bidding zones, paired with a constant balancing capacity (BC) demand for directions up and down per bidding zone. On the supply side, individual flexible generators (thermal and hydro) are modeled explicitly alongside time series per bidding zone for renewable generation. Storage units are not included in the current iteration of the study. Cross-zonal capacity is represented using ATC.

To analyze how input data quality matters for market optimization, the physical data on costs and capacities are kept completely static while the allowed bid format shifts across four specific scenarios:

- **Benchmark**: Raw model data, also called "combined bids", for all generators. These data are "the real costs" in our model.
- **Tree**: Linked bids in a tree structure of parent-child and other relations for all generators.
- **BB8h50**: Block bids of fixed block duration (8 hours) for half of the flexible generation assets, and linked bids for all other assets.
- **BB8h100**: Block bids of fixed block duration (8 hours) for all of the flexible generation assets.

The scenarios are run as a sequence of clear market actions. **First**, in the bid generation step, fundamental data on costs and capacities are transformed into market bids. **Second**, during bid selection, the market algorithm selects the bids that satisfy demand and network constraints at the lowest cost. **Third**, prices for energy and balancing capacity are calculated based on selected pricing rules.

Finally, for the purpose of our analysis, we perform welfare calculations using the cleared market volumes and the corresponding fundamental cost data. This step is key to understanding the true total costs and distributional outcomes, as the bid selection algorithm itself does not have access to the necessary fundamental data.

Note that while our day types (business, weekend) and four seasons are inspired by power market conditions during different days and seasons, they represent neither weekly nor yearly variation. They only serve to apply the model to varying conditions, and we aim to vary the input such that the results are relevant to actual conditions, at least for the particular CO2 emission price that we have used, or for our choice of any other parameter. However, our calculations may be rerun with other parameters and input data in order to explore other conditions.

4.2 Bid format impact on total costs

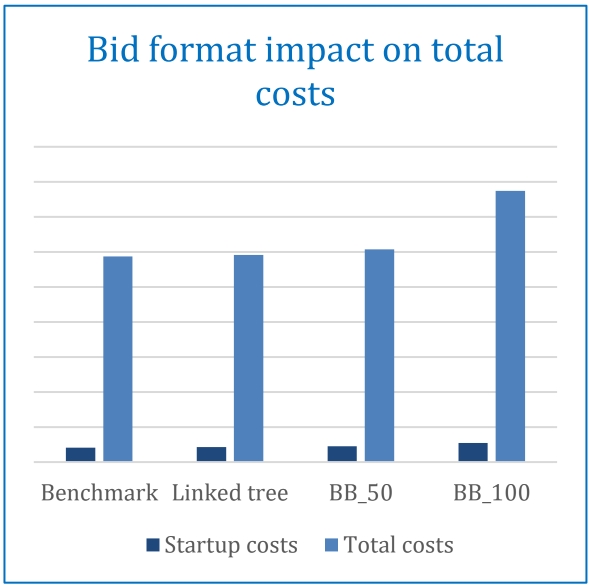


Figure 8 Bid format impact on total costs

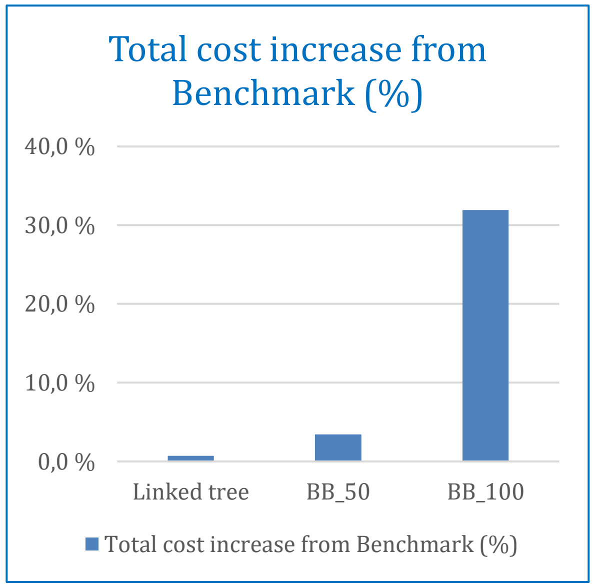


Figure 7 Total cost compared to benchmark

When serving our market algorithm bids on linked tree format (see chapter 3.4 for details), the total costs increase by 0.49% compared to our benchmark calculation with true costs. We estimate the cost increase to somewhere between 120 and 200 MEUR when applied to the SDAC volume of 2025[2]. When serving our market algorithm block bids (see chapter 3.4 for details) for half of all flexible generators and linked tree bids for all other assets, the total costs increase by 3.7% compared to our benchmark calculation (900 – 1500 MEUR when applied to the SDAC volume of 2025). When using block bids for all flexible generators and linked tree bids for all other assets, the total costs increase by 32% (7800 – 13000 MEUR when applied to the SDAC volume of 2025). We conclude that bid formats have a significant impact on the efficiency of our market model, that moderate use of block bids causes moderate damage to the resource allocation, and that dominant use of block bids causes drastic waste of fuel. This happens despite our block bid format offering flexibility in the amount of energy and balancing capacity to be selected for each MTU.

The startup costs stay at approximately 7% for all bid formats, they increase when total costs increase, but inefficient startups are not the main reason for the higher total costs.

[2] This estimate applies the 0.49% simulated increase to the annual physical fuel and resource costs within the SDAC footprint (estimated at 25–40 BEUR). This baseline considers that 60–65% of EU/EØS generation comes from zero-fuel sources, with remaining costs driven by current fuel and emission prices.

4.3 Bid format impact on redistribution

Feil! Fant ikke referansekilden. shows the total cost increase and changes in social surplus for our involved parties when different bid formats are used:

- Producer surplus (revenues from energy and BC markets minus total costs),
- Consumer surplus (reduction of the electricity bill)
- TSO surplus (reduction of the BC market expense).

Results in the figure are extrapolated from our eight days into a full year. The numbers are of limited interest, but the proportions may have a story to tell us. The main story is that inefficient market design increases total costs and, in most cases, prices as well, thereby shifting wealth from consumers to producers. The results were mixed across some of the eight days examined; however, in aggregate, prices rose in line with increases in cost.

Note that the distributional impact is greater than the total cost increase, i.e. the net inefficiency! Also, note that the change of total costs plus producer surplus equals the change of consumer surplus plus the TSO expense for balancing capacity!

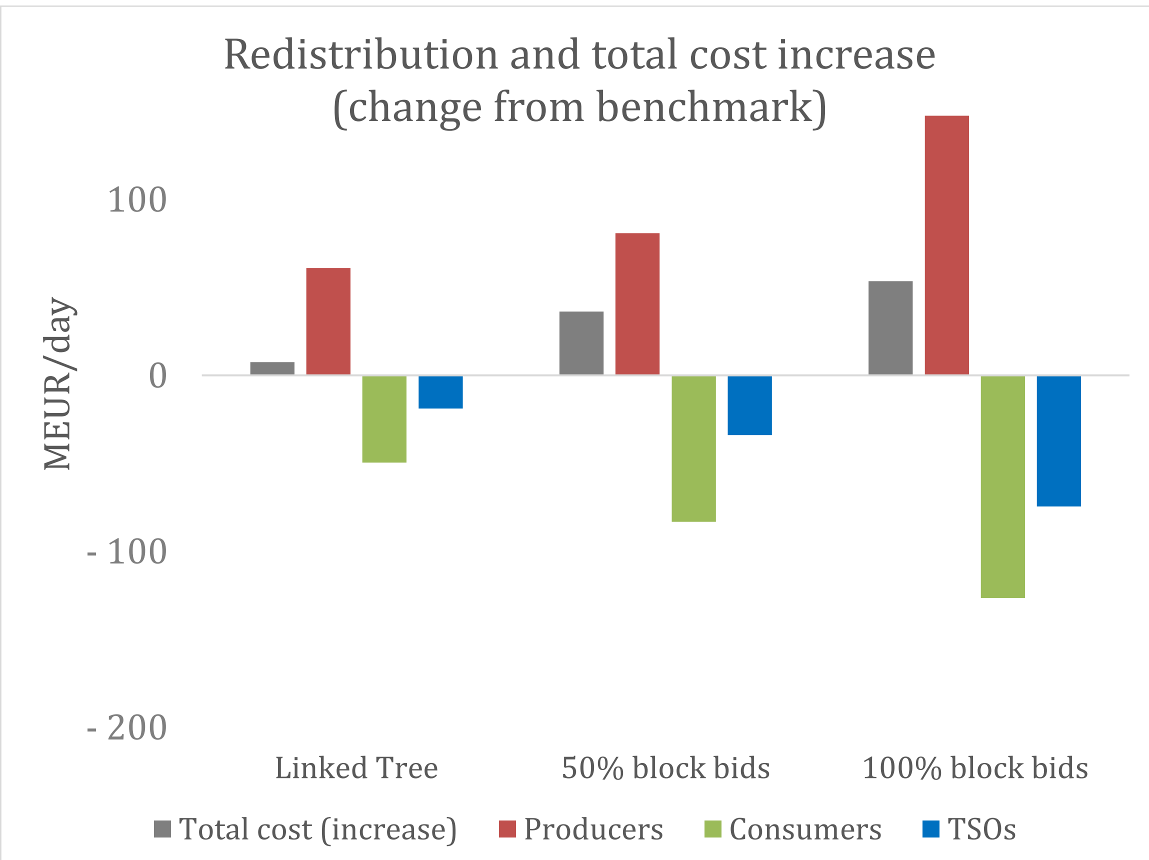


Figure 9 Distributional impacts vs. total cost increase

4.4 Additional simulations – other uses of the model

We applied the model on some additional tasks as described briefly below. Models of this type are essential in early-stage regulatory work to understand structural effects of market design that cannot be identified from historical data alone.

4.4.1 Global and regional balancing capacity exchange

We compared the total costs for three modes of balancing capacity exchange:

- Market-wide, i.e. freely among all bidding zones in our model and used for the main simulations described in this document.
- Regional, i.e. freely within three separate regions, each consisting of two or more bidding zones. The regions are defined for the purpose of the analysis only and shown in Figure 1.
- No balancing capacity exchange, i.e. all balancing capacity procured locally.

We used bids at linked tree format for this task, i.e. bids representing the cost structures .

Feil! Fant ikke referansekilden. shows the main observations. We found the market-wide benefit of BC exchange (~1%) lower than that of improving the bid formats (~3%). In particular, regional BC exchange seems to perform close to market-wide BC exchange. This does not exclude considerable benefit from BC exchange for some particular bidding zone.

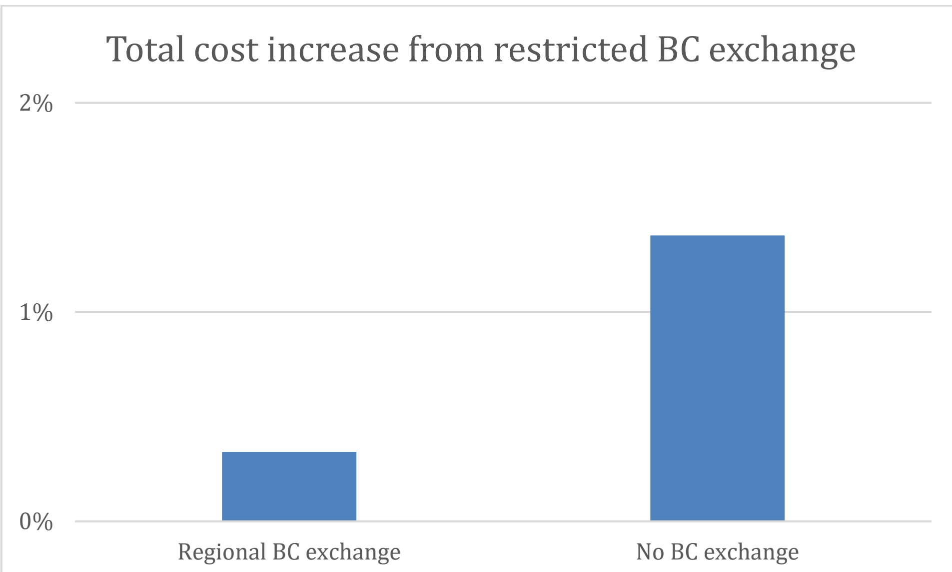


Figure 10 Regional BC exchange captures most of the benefits

4.4.2 Balancing capacity premium

Our simulations described elsewhere in this document use no "premium" in balancing capacity bids. When applying a uniform 5 EUR premium, we found no significant impact on total costs. The distributional impacts (volumes and prices) are not yet analyzed.

4.4.3 Balancing capacity costs

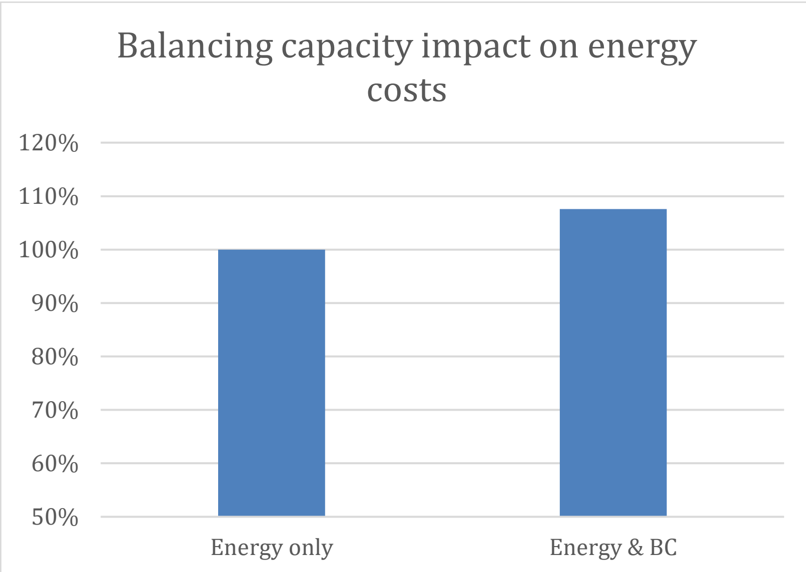


Figure 11 Balancing capacity costs

We applied market clearing with linked bids on two sets of balancing requirements:

- BC demand as described for co-optimization elsewhere in this document.
- BC demand equal to zero.

The total cost increased by 7% due to the balancing capacity demand. The number is less interesting than the use of a fundamental model to estimate the social costs of balancing capacity. Combined with an estimate of the marginal benefits of BC, this approach could be useful for the dimensioning of balancing capacity requirement.

4.4.4 Bid formats in an energy only market

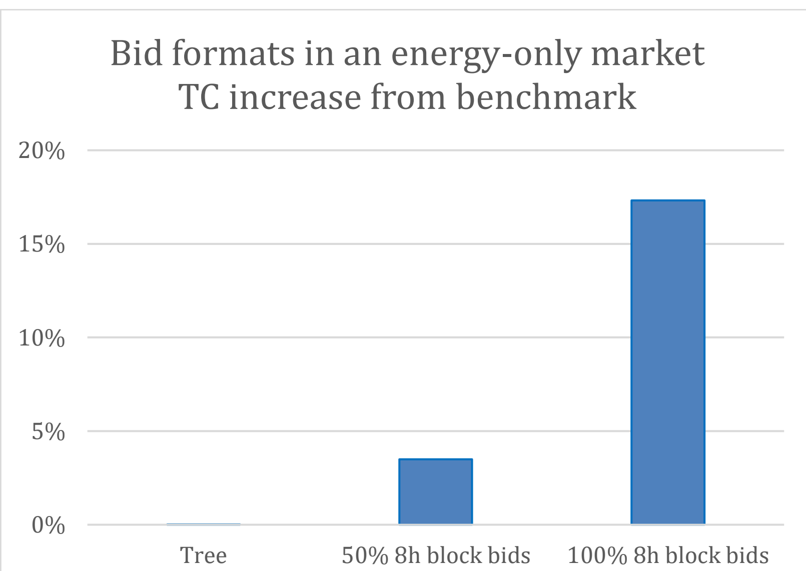


Figure 12 Bid format impact in an energy only market

When applying the different bid formats to an energy-only optimization, we got results that are similar to those of the co-optimized problem: Linked tree bids perform well, while increasing use of block bids inflates total costs correspondingly.

5 Conclusions

5.1 On the topic

Bid formats are important for the efficiency of a market mechanism. The accuracy of an algorithm depends on the input data quality. This may seem obvious, but the matter receives little attention in the research and development of power market design.

Our simulations show that complex cost structures of power and balancing capacity can be represented by linked bids. Further, the simulations show that block bids are not fit for the purpose – the combined impact of reduced algorithmic flexibility and reduced information on the cost structure causes significant or even drastic increase in total energy costs. This applies to the joint clearing of balancing capacity and energy markets, as well as to energy-only markets.

We used a model inspired by the one used in ACER's Co-optimization Benefit Study (2024), and found inefficiencies from bid formats far greater than the estimated gains of joint clearing of energy and balancing capacity.

We also found that the increase of total costs due to inaccurate input data causes higher market prices on average, and a redistribution of wealth from consumers to producers.

Our main takeaways from the analysis are these:

- Power market design development should focus on elements that may bring significant benefits. This might not be the joint clearing of energy and balancing capacity markets unless bid formats are redesigned. Joint clearing based on inefficient bid formats may reduce the ability for a region to introduce more efficient bid formats.
- Costly and complex market development projects with little or dubious benefit undermine the legitimacy and trust of European market integration.

5.2 On the tool

We found that a fundamental market model including bids that capture non-convex supply costs of energy and balancing capacity can indeed be developed with modest efforts, and that it can offer insights on market performance and outcomes that cannot be achieved from cost-based models and even less by simulations using historical bids with no knowledge of fundamental costs.

We argue that such models are necessary and should be applied in the early phase of regulatory development, as they isolate design choices, reveal structural effects, and expose fundamental challenges long before development and implementation. This is essential to guide future design choices.

5.3 Further work

Our analysis can be seen as a comparison of "good co-optimization" with "bad co-optimization". While our focus has been on the need for good algorithmic input in order to get efficient resource allocation, we wish to explore pricing methods and redistribution aspects further. Also, we intend to expand the model to sequential clearing of balancing capacity and energy, thus facilitating analysis of "co-optimization or not", which was the topic of ACER's Co-optimization Benefit Study. A sequential clearing model with market bids on different bid formats would also facilitate analysis of pure balancing capacity market matters, relevant for the European work following the Harmonized CZCA Methodology.

6 Selected references

- ACER. (2024). Welfare Benefits of Co-Optimising Energy and Reserves.
  Agency for the Cooperation of Energy Regulators (ACER).
  https://www.acer.europa.eu/sites/default/files/documents/Publications/ACER_Cooptimisation_Benefits_Study_2024.pdf
- European Commission. (2015). Commission Regulation (EU) 2015/1222 establishing a Guideline on Capacity Allocation and Congestion Management (CACM).
- European Commission. (2017). Commission Regulation (EU) 2017/2195 establishing a Guideline on Electricity Balancing (EBGL).
- Gomory, R. E., & Baumol, W. J. (1960). Integer Programming and Pricing. Econometrica, 28(3), 521–550.
- Scarf, H. E. (1994). The Allocation of Resources in the Presence of Indivisibilities. Journal of Economic Perspectives, 8(4), 111–128.
- Van Vyve, M. (2011). Linear Prices for Non-Convex Electricity Markets. CORE Discussion Paper 2011/50.

Appendices

A. Mathematical formulation of the MILP objective function.

The unit commitment model

The Combined Bids strategy clears energy and all balancing products simultaneously using a single Mixed-Integer Linear Programme (MILP). Generator commitment and dispatch decisions, piecewise cost curves, startup costs, reserve provision, cross-zonal flows, and storage are all modelled in one optimisation step.

Indexed sets

Symbol	Definition
G	Set of generators, indexed by g
$T = \{0, \ldots, H-1\}$	Set of time periods (hours), indexed by t
R	Set of bidding zones (regions), indexed by r
$W = \{0,1,2,3,4\}$	Piecewise breakpoints per generator, indexed by w
$Z = \{0,1,2,3\}$	Piecewise intervals per generator, indexed by z

Parameters

Symbol	Definition
$\bar{p}g$	Maximum output of generator g (MW)
$\underline{p}g$	Minimum stable output (must-run level) of generator g (MW)
$\varphi g,t$	Availability profile of generator g in period t ∈ [0,1]; equals 1 for fully dispatchable units
$bp^{P}g,w$	Power quantity at breakpoint w on the cost curve of generator g (MW)
$bp^{c}g,w$	Variable cost coefficient at breakpoint w (€/MWh)
SCg	Startup cost of generator g (€)
$\bar{a}^{afRR}g$	aFRR capacity limit as a fraction of $\bar{p}g \cdot \varphi g,t$
$\bar{a}^{mfRR}g$	mFRR capacity limit as a fraction of $\bar{p}g \cdot \varphi g,t$
$balg \in \{1,2\}$	Unit type: 1 = fast (can offer mFRR offline), 2 = slow (must be online for mFRR), 0 = no reserve
$D^{E}r,t$	Energy demand in zone r, period t (MW)
$D^{a+}r,t$	aFRR upward reserve requirement in zone r, period t (MW)
$D^{a-}r,t$	aFRR downward reserve requirement (MW)
$D^{m+}r,t$	mFRR upward reserve requirement (MW)

$D^{m-}_{r,t}$	mFRR downward reserve requirement (MW)
$NTC_{r,r'}$	Net transfer capacity from zone r to zone r' (MW); 0 if no link
$ntc^{cap}_{r,r'}$	Scalar CZC availability multiplier for capacity products on link r→r'
α	Fraction of NTC allocated to reserve capacity (czc_share), default 0.2
β	Minimum fraction of reserve demand to be met by local generators (local_balance)
$VOLL^{E}$	Value of lost energy demand (€/MWh)
$VOLL^{Bc}$	Value of unserved reserve demand (€/MW·h)
S_g, S^{init}_g	Storage capacity (MWh) and initial state-of-charge fraction (storage units only)
η_g	Round-trip charging efficiency (storage units only)

Decision variables

Symbol	Definition
$p_{g,t} \geq 0$	Energy production of generator g in period t (MW)
$u_{g,t} \in \{0,1\}$	Commitment status: 1 if generator g is online in period t
$s_{g,t} \geq 0$	Startup indicator for generator g in period t (equals 1 at each startup)
$\lambda_{g,t,w} \in [0,1]$	Weight assigned to breakpoint w in the piecewise cost curve
$\delta_{g,t,z} \in \{0,1\}$	Interval selector: 1 if the operating point lies in interval z
$r^{a+}_{g,t} \geq 0$	aFRR upward reserve provided by generator g, period t (MW)
$r^{a-}_{g,t} \geq 0$	aFRR downward reserve provided by generator g, period t (MW)
$r^{m+}_{g,t} \geq 0$	mFRR upward reserve provided by generator g, period t (MW)
$r^{m-}_{g,t} \geq 0$	mFRR downward reserve provided by generator g, period t (MW)
$f^{E}_{r,r',t} \geq 0$	Energy flow from zone r to zone r', period t (MW)
$f^{a}_{r,r',t} \geq 0$	Total aFRR capacity reservation on link r→r', period t (MW)
$f^{a+}_{r,r',t} \geq 0$	aFRR upward flow on link r→r', period t (MW)
$f^{a-}_{r,r',t} \geq 0$	aFRR downward flow on link r→r', period t (MW)
$f^{m}_{r,r',t} \geq 0$	Total mFRR capacity reservation on link r→r', period t (MW)
$f^{m+}_{r,r',t} \geq 0$	mFRR upward flow on link r→r', period t (MW)
$f^{m-}_{r,r',t} \geq 0$	mFRR downward flow on link r→r', period t (MW)
$ls^{E}_{r,t} \geq 0$	Energy load shedding in zone r, period t (MW); penalised slack

$ls^{a+}_{r,t}, ls^{a-}_{r,t}, ls^{m+}_{r,t}, ls^{m-}_{r,t} \geq 0$	Reserve load shedding by product type (MW)
$E^{res}_{g,t} \geq 0$	Hydraulic reservoir level (MWh), reservoir generators only
$E^{stor}_{g,t} \geq 0$	Battery storage level (MWh), storage generators only
$c_{hg,t} \geq 0$	Storage charging power (MW), storage generators only

Objective Function

Minimise total variable cost, startup cost, CZC flow cost, and penalised load shedding across all generators and periods:

$$\min \ \Sigma_{\{g,t,w\}} \ \lambda_{g,t,w} \cdot bp^c_{g,w} \cdot bp^P_{g,w} \cdot \varphi_{g,t} \quad \text{(variable cost)}$$
$$+ \Sigma_{\{g,t\}} \ s_{g,t} \cdot SC_g \quad \text{(startup cost)}$$
$$+ \Sigma_{\{r,r',t\}} \ (f^E_{r,r',t} + f^a_{r,r',t} + f^m_{r,r',t}) \cdot 0.001 \quad \text{(CZC cost)}$$
$$+ VOLL^E \cdot \Sigma_{\{r,t\}} \ ls^E_{r,t} \quad \text{(energy load shedding penalty)}$$
$$+ VOLL^{Bc} \cdot \Sigma_{\{r,t\}} \ (ls^{a+}_{r,t} + ls^{a-}_{r,t} + ls^{m+}_{r,t} + ls^{m-}_{r,t}) \quad \text{(reserve load shedding penalty)}$$

Note: The variable cost term is the inner product of piecewise weights with breakpoint power and cost. A small symbolic cost on CZC flows prevents the solver from routing unnecessary cross-border flows when multiple optimal solutions exist. VOLL values are set very high to ensure feasibility takes priority.

Constraints

Piecewise-linear cost curve (SOS2 representation)

Each generator's fuel cost is represented by a piecewise-linear function of output with up to five breakpoints. The Special Ordered Set of type 2 (SOS2) conditions ensure that at most two adjacent breakpoints are active simultaneously, faithfully representing non-linear cost curves within an LP/MILP framework.

Constraint	Expression	Description
Power link	$p_{g,t} = \Sigma_w \ \lambda_{g,t,w} \cdot bp^P_{g,w} \cdot \varphi_{g,t}$	*Links production to the weighted sum of breakpoint quantities.*
Weight sum	$\Sigma_{\{w: bp^P_{g,w}>0\}} \ \lambda_{g,t,w} = u_{g,t}$	*Weights on non-zero breakpoints sum to the commitment status; forces pg,t = 0 when ug,t = 0.*
Interval sum	$\Sigma_z \ \delta_{g,t,z} = u_{g,t}$	*Exactly one interval is active when committed; none when offline.*
Adjacency w = 0	$\lambda_{g,t,0} \leq \delta_{g,t,0}$	*First weight active only if first interval is active.*
Adjacency w = W	$\lambda_{g,t,W} \leq \delta_{g,t,W-1}$	*Last weight active only if last interval is active.*
Adjacency (other)	$\lambda_{g,t,w} \leq \delta_{g,t,w-1} + \delta_{g,t,w}$	*Interior weight active only if one of its two adjacent intervals is active.*

Generation output bounds

Constraint	Expression	Description
Max output	$p_{g,t} \leq \bar{p}_g \cdot \varphi_{g,t} \cdot u_{g,t}$	*Output cannot exceed the capacity available in the current period.*

Min output	$p_{g,t} \geq \underline{p}_g \cdot \varphi_{g,t} \cdot u_{g,t}$	*When committed, output must be at or above the minimum stable level.*

Reserve headroom constraints

Generator units are classified by their speed of response. Fast units (balg = 1) can precommit mFRR upward reserve without being online (they can start within the mFRR delivery window). Slow units (balg = 2) must be committed to offer mFRR. All reserve-eligible units must stay within their physical capacity envelope.

Constraint	Expression	Description
Fast — aFRR headroom	$p_{g,t} + r^{a+}_{g,t} \leq \bar{p}_g \cdot u_{g,t}$	*aFRR up reserve plus production cannot exceed online capacity (fast units, balg = 1).*
Fast — total headroom	$p_{g,t} + r^{a+}_{g,t} + r^{m+}_{g,t} \leq \bar{p}_g$	*Fast units may offer mFRR when offline; total cannot exceed absolute pmax.*
Slow — total headroom	$p_{g,t} + r^{a+}_{g,t} + r^{m+}_{g,t} \leq \bar{p}_g \cdot u_{g,t}$	*Slow units must be committed to offer any upward reserve (balg = 2).*
Down headroom	$p_{g,t} - r^{a-}_{g,t} - r^{m-}_{g,t} \geq \underline{p}_g \cdot u_{g,t} \cdot \varphi_{g,t}$	*Downward reserve headroom: net output after reserve provision must stay above minimum load.*
aFRR up limit	$r^{a+}_{g,t} \leq \bar{p}_g \cdot \bar{a}^{afRR}_g \cdot \varphi_{g,t}$	*aFRR upward reserve is capped at a fixed fraction of available capacity.*
aFRR down limit	$r^{a-}_{g,t} \leq \bar{p}_g \cdot \bar{a}^{afRR}_g \cdot \varphi_{g,t}$	*aFRR downward reserve capacity limit.*
mFRR up limit	$r^{m+}_{g,t} \leq \bar{p}_g \cdot \bar{a}^{mfRR}_g \cdot \varphi_{g,t}$	*mFRR upward reserve is capped at a fixed fraction of available capacity.*
mFRR down limit	$r^{m-}_{g,t} \leq \bar{p}_g \cdot \bar{a}^{mfRR}_g \cdot \varphi_{g,t}$	*mFRR downward reserve capacity limit.*

Commitment and startup dynamics

Constraint	Expression	Description
Startup detection	$s_{g,t} \geq u_{g,t} - u_{g,t-1}, \quad t > 0$	*Forces startup variable to 1 whenever a unit transitions from offline to online.*
Initial startup (cold)	$s_{g,0} \geq u_{g,0} \text{ if starting} = 1$	*Unit was not running before the horizon; any commitment in hour 0 incurs startup cost.*
Initial startup (hot)	$s_{g,0} = 0 \text{ if starting} = 0$	*Unit was already running; no startup cost in hour 0.*
Startup cap	$s_{g,t} \leq 1$	*Ensures startup is counted at most once per commitment transition.*

Note: Minimum up-time and down-time constraints, as well as ramp-rate limits, are defined in the codebase (dynamics.py) but are not currently active in the default configuration. They can be enabled to tighten the model if required.

Market demand balance

Supply must meet demand in each zone and period. The notation Gr denotes the set of generators located in zone r. Net imports add cross-zonal inflows minus outflows. Load-shedding provides a penalised slack that keeps the problem feasible under extreme scenarios.

Constraint	Expression	Description
Energy balance	$\Sigma\{g\in Gr\}\ pg,t + \Sigma r'\ f^{E}r',r,t - \Sigma r'\ f^{E}r,r',t + ls^{E}r,t = D^{E}r,t$	*Nodal energy balance: generation plus net imports equals demand.*
aFRR up	$\Sigma\{g\in Gr\}\ r^{a+}g,t + \Sigma r'\ f^{a+}r',r,t - \Sigma r'\ f^{a+}r,r',t \geq D^{a+}r,t - ls^{a+}r,t$	*aFRR upward reserve supply must meet requirement (inequality allows over-provision).*
aFRR down	$\Sigma\{g\in Gr\}\ r^{a-}g,t + \Sigma r'\ f^{a-}r',r,t - \Sigma r'\ f^{a-}r,r',t \geq D^{a-}r,t - ls^{a-}r,t$	*aFRR downward reserve supply must meet requirement.*
mFRR up (combined)	$\Sigma\{g\in Gr\}(r^{m+}g,t+r^{a+}g,t) + \text{net CZC (aFRR up + mFRR up)} = D^{m+}r,t+D^{a+}r,t - ls^{a+}r,t - ls^{m+}r,t$	*Combined aFRR+mFRR upward balance: aFRR provision counts toward mFRR since faster reserves always qualify. Equality constraint.*
mFRR down (combined)	$\Sigma\{g\in Gr\}(r^{m-}g,t+r^{a-}g,t) + \text{net CZC (aFRR down + mFRR down)} = D^{m-}r,t+D^{a-}r,t - ls^{a-}r,t - ls^{m-}r,t$	*Combined aFRR+mFRR downward balance; mirrors the upward constraint.*
Local up reserve	$\Sigma\{g\in Gr\}(r^{m+}g,t+r^{a+}g,t) \geq \beta\cdot(D^{m+}r,t+D^{a+}r,t) - ls^{a+}r,t - ls^{m+}r,t$	*A minimum fraction β of the combined upward reserve demand must be sourced from within the zone.*
Local down reserve	$\Sigma\{g\in Gr\}(r^{m-}g,t+r^{a-}g,t) \geq \beta\cdot(D^{m-}r,t+D^{a-}r,t) - ls^{a-}r,t - ls^{m-}r,t$	*Minimum local fraction for downward reserve; mirrors local up constraint.*

Cross-zonal capacity constraints

Cross-zonal capacity links are characterised by a net transfer capacity (NTC). Energy flow and reserve capacity reservation compete for the same link. The parameter α controls how much NTC may be used for reserve products.

Constraint	Expression	Description
Combined link limit	$f^{E}r,r',t + f^{a}r,r',t + f^{m}r,r',t \leq NTCr,r'$	*Total use of link r→r' for energy and capacity reservation cannot exceed NTC. Applies only if NTC > 0.*
BC capacity share	$f^{a}r,r',t + f^{m}r,r',t \leq \alpha \cdot NTCr,r' \cdot ntc^{cap}r,r'$	*Reserve capacity reservation is limited to a fraction α of NTC, scaled by the BC availability multiplier.*
aFRR up coverage	$f^{a}r,r',t \geq f^{a+}r,r',t$	*Total aFRR reservation on link r→r' must cover the aFRR upward flow in that direction.*
aFRR down coverage	$f^{a}r,r',t \geq f^{a-}r',r,t$	*Total aFRR reservation on r→r' must also cover downward flow in the reverse direction; both directions compete for the same physical link.*
mFRR up coverage	$f^{m}r,r',t \geq f^{m+}r,r',t$	*mFRR reservation on link r→r' must cover mFRR upward flow.*
mFRR down coverage	$f^{m}r,r',t \geq f^{m-}r',r,t$	*mFRR reservation on r→r' must cover mFRR downward flow from the opposite direction.*

Bid Selector Model

The Bid Selector strategy generates a structured bid tree for each generator and then selects which bids to accept in a second MILP. Each generator is represented by a hierarchy of standardised bid types: Startup Cost (SC), Minimum Load (ML/EMIN), Additional Load (AL/E), and reserve capacity bids (BCU for upward, BCD for downward). The parent-child structure enforces generator commitment logic without requiring explicit binary commitment variables separate from the bid acceptance decision.

Bid Types and Hierarchy

Bid Type	Description
SC	Startup Cost bid — one per generator, covers the cost of starting the unit
ML (EMIN)	Minimum Load bid — one per generator per hour, indivisible (quantity = Pmin)
AL (E)	Additional Load bid — one per price-quantity segment per hour, divisible
BCU	Balancing Capacity Upward bid — one per hour, child of AL, represents upward reserve capacity
BCD	Balancing Capacity Downward bid — one per hour, child of AL, represents downward reserve capacity

The hierarchy is SC → ML → AL → BCU/BCD. A child bid can only be accepted if its parent is accepted. BCU and BCD are mutually exclusive with the AL bid for the same generator and hour: a generator either dispatches additional energy (AL) or reserves that headroom for balancing (BCU/BCD).

Indexed Sets

Symbol	Definition
B	Set of all bids, indexed by b
$A \subseteq B$	Set of SC bids, one per generator (indexed by a); defines the generator-level dimension
$T = \{1,\ldots,H\}$	Set of hours, indexed by t
Z	Set of bidding zones, indexed by z
$P = \{E, U, D\}$	Set of products: E = Energy, U = Up (BCU), D = Down (BCD)
parent(b)	Parent bid of bid b in the hierarchy (undefined for SC bids)
AL-sibling(b)	The AL bid that shares a parent with BCU/BCD bid b (used in mutual exclusion)

Parameters

Symbol	Definition
qb	Quantity (MW) of bid b; for SC bids a symbolic minimum quantity MINQ is used

πb	Price (€/MW) for variable bids; (€) for startup cost bids
Dz,p,t	Demand for product p ∈ P in zone z, hour t (MW)
β^{loc}	Local sourcing fraction: minimum share of reserve demand to be met locally
$NTCz,z'$	CZC energy limit between zones z and z' (MW)
α^{czc}	Share of NTC available for BC products (CZC_for_bc)
$\lim^{Bc}z,z'$	Scalar availability multiplier for BC CZC on link z→z'
Cp	Penalty cost (€/MW·h) per unit of unserved demand for product p
$on_0 a \in \{0,1\}$	Starting status of generator a: 0 = already running, 1 = not yet started

Decision Variables

Symbol	Definition
$xb \in \{0,1\}$	Bid acceptance: 1 if bid b is accepted, 0 otherwise
$vb \geq 0$	Accepted volume for bid b (MW)
$ua,t \in \{0,1\}$	Commitment status of generator a in hour t
$sa,t \in \{0,1\}$	Startup indicator for generator a in hour t
$f^{E}z,z',t \geq 0$	Energy CZC flow from zone z to z', hour t (MW)
$f^{Bc}z,z',t \geq 0$	Total reserve capacity CZC reservation on link z→z' (MW)
$f^{BcU}z,z',t \geq 0$	Upward reserve (BCU) flow on link z→z' (MW)
$f^{BcD}z,z',t \geq 0$	Downward reserve (BCD) flow on link z→z' (MW)
$\ell z,p,t \geq 0$	Lost demand for product p in zone z, hour t (MW); penalised slack

Objective Function

Minimise total variable cost plus startup cost plus CZC friction cost plus unserved demand penalty:

$$\min\ \Sigma\{b\text{: type}(b)\neq SC\}\ vb \cdot \pi b \quad \text{(variable dispatch cost)}$$
$$+\ \Sigma\{a\in A,\ t\}\ sa,t \cdot \pi^{Rc}a \quad \text{(startup cost)}$$
$$+\ \Sigma\{z,z',t\}\ (\ f^{E}z,z',t + f^{Bc}z,z',t\ ) \cdot 0.001 \quad \text{(CZC cost)}$$
$$+\ \Sigma\{z,p,t\}\ \ell z,p,t \cdot Cp \quad \text{(unserved demand penalty)}$$

Constraints

Bid hierarchy (parent-child acceptance)

Constraint	Expression	Description

Parent-child	$x_b \le x_{parent(b)} \quad \forall b$ with a defined parent	*A child bid can only be accepted if its parent is accepted. This is the tree's core structural constraint: ML requires SC, AL requires ML, BCU/BCD require AL.*
BC mutual exclusion with AL	$x_b \le x_{parent(b)} - x_{AL\text{-}sibling(b)} \quad \forall b$ of type BC	*A BCU or BCD bid can only be accepted if the parent AL bid is accepted but the AL energy dispatch is not also accepted. A generator either dispatches additional energy or reserves capacity — not both.*

Accepted volume bounds

Constraint	Expression	Description
Volume upper bound	$v_b \le x_b \cdot q_b$	*Accepted volume cannot exceed the bid quantity when the bid is accepted, and is zero when the bid is rejected.*
Volume lower bound (ML/EMIN)	$v_b \ge x_b \cdot q_b \quad \forall b$ of type EMIN	*Minimum Load bids are indivisible: if accepted, the full quantity Pmin must be dispatched.*
Volume lower bound (others)	$v_b \ge x_b \cdot \varepsilon \quad \forall b$ not EMIN	*All other bids are divisible; a token lower bound $\varepsilon > 0$ prevents numerical degeneracy.*

Parent-child volume linkage

These constraints enforce consistency between a child bid's accepted volume and its parent's dispatch. They are applied to energy (AL) and downward reserve (BCD) bids.

Constraint	Expression	Description
Energy children (AL)	$x_b \le v_{parent(b)} / q_{parent(b)} \quad \forall b$ with Energy product	*An AL bid can only be activated if the parent ML bid is dispatched. The right-hand side equals 1 when ML is fully dispatched and 0 when ML is rejected, giving the link between volumes.*
Down reserve children (BCD)	$v_b \le q_b - (q_{parent(b)} - v_{parent(b)}) \quad \forall b$ of product type Down	*BCD capacity is the portion of AL capacity that is NOT dispatched as energy. If the parent AL is dispatched at v_{AL} out of q_{AL} MW, then $q_{AL}-v_{AL}$ MW of headroom is available for downward reserve, and the BCD volume is bounded accordingly.*

Note: No corresponding upward volume linkage exists in the base formulation: BCU volume is constrained only by the upper bound (gen_bounds_max_con) and the mutual exclusion with AL. An additional big-M constraint can be added to bound BCU volume to the AL dispatch level, which tightens the relaxation.

Asset commitment and startup

Constraint	Expression	Description
Commitment link	$x_{ML,b} = u_{parent\text{-}SC(b), t(b)} \quad \forall$ ML bids b	*Acceptance of a Minimum Load bid is equivalent to the generator being committed*

		in that hour. The binary variable ua,t is defined over generator-hour pairs and connects the bid structure to the unit-level commitment state.
Startup (t > 1)	$sa,t \geq ua,t - ua,t{-}1$	*Startup indicator is forced to 1 whenever commitment status changes from 0 to 1 (offline to online transition).*
Startup (t = 1, cold)	$sa,1 \geq ua,1 \quad \text{if } on_0a = 1$	*If the generator was not running before the planning horizon, any commitment in hour 1 triggers a startup.*
Startup (t = 1, hot)	$sa,1 = 0 \quad \text{if } on_0a = 0$	*If the generator was already running at the start, no startup cost is incurred for the first hour.*

Block Bids

Some generators submit bids as indivisible blocks — a group of hourly bids that must all be accepted or all rejected together (e.g. a must-run unit with a fixed block structure).

Constraint	Expression	Description
Block consistency	$x\_\{b_1\} = x\_\{b_2\} \quad \forall(b_1, b_2)$ in same block	*All bids within a block are tied together: the model cannot accept some hours within a block while rejecting others.*

Mutual exclusivity

Constraint	Expression	Description
Exclusivity	$x\_\{b_1\} + x\_\{b_2\} \leq 1 \quad \forall$ exclusive pairs (b_1, b_2)	*At most one bid from an exclusive pair can be accepted. Exclusive pairs are defined in the bid input data and typically represent alternative dispatch options for the same asset.*

Cross-zonal capacity constraints

Constraint	Expression	Description
CZC combined limit	$f^{E}z,z',t + f^{Bc}z,z',t \leq NTCz,z' \quad \forall z \neq z'$	*Total use of link z→z' for energy and reserve capacity cannot exceed the NTC.*
BC limit	$f^{Bc}z,z',t \leq NTCz,z' \cdot \alpha^{czc} \cdot \lim^{Bc}z,z'$	*Reserve capacity reservation is limited to a fraction α^{czc} of NTC, scaled by the link-specific BC multiplier.*
BCU decomposition	$f^{Bc}z,z',t \geq f^{BcU}z,z',t$	*Total BC reservation covers the upward reserve flow in that direction.*
BCD decomposition	$f^{Bc}z,z',t \geq f^{BcD}z',z,t$	*Total BC reservation on z→z' also covers the downward flow arriving from z' (both*

		directions share the same physical link capacity).

Market demand balance

The set $B_{\{z,p,t\}}$ denotes bids (excluding SC bids) whose area, product, and hour match (z, p, t).

Constraint	Expression	Description
Energy balance	$\Sigma_{\{b\in B_{\{z,E,t\}}\}} v_b + \Sigma_{z'} f^{E}_{z',z,t} - \Sigma_{z'} f^{E}_{z,z',t} + \ell_{z,E,t} = D_{z,E,t}$	*Total accepted energy volumes plus net imports plus lost demand must equal the energy demand target in each zone and hour.*
Up reserve balance	$\Sigma_{\{b\in B_{\{z,U,t\}}\}} v_b + \Sigma_{z'} f^{BcU}_{z',z,t} - \Sigma_{z'} f^{BcU}_{z,z',t} + \ell_{z,U,t} = D_{z,U,t}$	*Accepted BCU volumes plus net upward reserve imports must meet the BCU demand target.*
Down reserve balance	$\Sigma_{\{b\in B_{\{z,D,t\}}\}} v_b + \Sigma_{z'} f^{BcD}_{z',z,t} - \Sigma_{z'} f^{BcD}_{z,z',t} + \ell_{z,D,t} = D_{z,D,t}$	*Accepted BCD volumes plus net downward reserve imports must meet the BCD demand target.*
Local reserve (up)	$\Sigma_{\{b\in B_{\{z,U,t\}}\}} v_b + \ell_{z,U,t} \geq \beta^{loc} \cdot D_{z,U,t}$	*At least a fraction β^{loc} of the upward reserve demand must be covered by local generators, without relying on cross-zonal imports.*
Local reserve (down)	$\Sigma_{\{b\in B_{\{z,D,t\}}\}} v_b + \ell_{z,D,t} \geq \beta^{loc} \cdot D_{z,D,t}$	*Mirrors the local up requirement for downward reserve.*

B. Calculation of market prices

The calculation of market prices is independent of bid format choice (combined bids vs. linked trees and block bids). The methodology, steps, underlying rules, and objective function remain consistent regardless of format. Accordingly, the outputs of the market clearing process are standardized before being used as inputs to the pricing module: the format is asset-based, with all bids associated with a given asset aggregated together and costs found based on total energy output and each assets corresponding cost curve.

Energy prices and balancing capacity prices are determined sequentially, energy prices are calculated first, followed by balancing capacity prices, which are derived from the resulting energy prices.

Energy Prices

Energy prices are derived from a market clearing that uses energy-only demand, with an additional ½ BCU demand incorporated into the original energy demand for each bidding zone and MTU (the rationale for this adjustment is detailed in Chapter 3.6.1). Once bids and assets have been selected (determining the MTU and corresponding volume/cost), market prices are estimated by solving an optimization problem that minimizes total payout (price multiplied by selected volume for each asset). Three rules govern this process:

Constraint	Expression	Description
In-the-money constraint	Price(r,t) ≥ MC(a,t)	*Price in region r at MTU t must be greater than or equal to marginal cost for asset a (in bidding zone r) and MTU t). MC is calculated based on volume selected for each asset including start-up costs*
Price follows trade direction	Price(import_region,t) ≥ Price(export_region,t)	*Where energy is exchanged across a border, the price in the importing bidding zone must be greater than or equal to the price in the exporting bidding zone.*
Equal price for uncongested areas	Price(r,t) = Price(r',t)	*If the trade of energy on line between r and r' is not at full capacity, the two areas are considered uncongested and should have the same price*

All selected assets (i.e., those with an accepted volume greater than zero) must remain in-the-money in every hour. The cost per MW reflects the selected volume as well as start-up costs, amortized across all MTUs to which the start-up applies. This constraint applies uniformly across each MTU, including for linked tree bids and block bids.

It can reasonably be argued that both the start-up cost treatment and the block bid design do not represent the theoretically optimal approach to price estimation. However, these design choices improve the interpretability, consistency, and stability of resulting prices, and help avoid extreme price outcomes that can otherwise arise from corner cases where the linear programming model identifies a marginally better total payout at the expense of economically meaningful prices. As this study does not focus on pricing design per se, the priority was placed on producing prices that are understandable, consistent, and stable.

The rule requiring prices to follow the direction of export is straightforward to apply. The third rule concerning equal prices in uncongested areas is more difficult to implement in practice, despite being consistent with standard economic theory. In principle, if trade across a line is not constrained by capacity, prices on either side should be equal; however, determining whether trade is genuinely capacity-constrained is non-trivial in the presence of non-convexities. In the Nordic aFRR and mFRR capacity market algorithm, identifying these uncongested borders is a complex undertaking that requires re-running the market clearing to assess whether a given line is binding. For the purposes of this study, a simplified approach is adopted: a line is considered congested if trade on it reaches maximum capacity. While this simplification does not fully account for factors such as minimum production constraints and block bids, it provides a consistent and easily interpretable rule suited to the scope of this study.

Within this optimization problem, prices are treated as decision variables, with inputs (accepted bids and cross-border trade) derived from the results of the energy-only-plus-½-bcu-demand market clearing.

Balancing capacity prices

Once energy prices have been determined, they are used to calculate the producer surplus from energy for each asset providing balancing capacity in each MTU. This producer surplus is then compared against the optimal producer surplus achievable through energy-only dispatch at these prices, calculated by solving an optimization problem for each asset against the established prices.

The difference between these two producer surplus values in each MTU, divided by the offered balancing capacity (both upward and downward), yields the opportunity cost of providing balancing capacity for each asset and MTU. The final balancing capacity price for both upward and downward capacity is set as the maximum of these opportunity cost values within each bidding zone and MTU.

Price spreading of balancing prices follows same logic as for energy prices above.

C. Generator types and fuel costs

Thermal generation costs and startup used in our model are shown below. They correspond to a CO_2 emission cost of 78 EUR/t. The startup costs represent heat loss and mechanical wear.

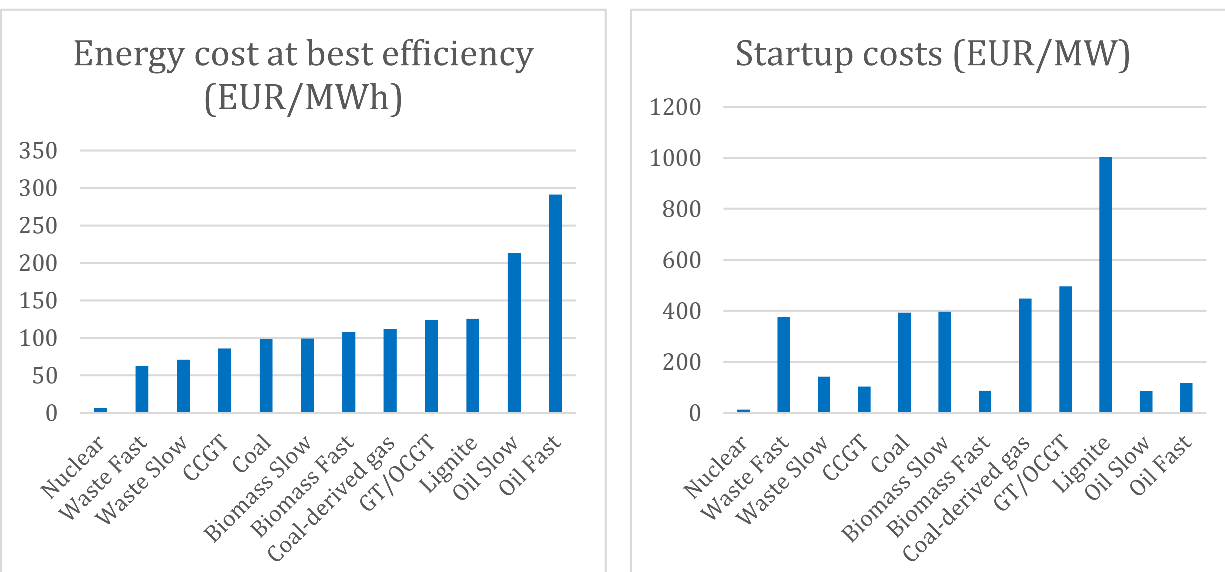


Figure 13 Fundamental costs

Water values are exogenous in our model. The reservoir hydropower capacity is split on five types in order to represent different different levels of yearly full-load hours and flexibility in adaptation to market prices. For each season, we choose the water values by references to thermal generation costs.

Table 2 Water values

WaterValueType	Summer	Fall	Winter	Spring
h_11	Nuclear	Waste Fast	Waste Fast	Nuclear

h_12	Nuclear	Waste Fast	Coal	Waste Fast
h_21	Waste Fast	CCGT	CCGT	CCGT
h_22	Waste Fast	CCGT	GT/OCGT	CCGT
h_31	Coal	GT/OCGT	Oil Slow	Coal

Startup costs for hydropower are set at a uniform 3 EUR/MW, representing mechanical wear.

D. Generation mix by technology and bidding zone

Table 3 Generation mix per bidding zone

Generation mix by technology and bidding zone (MW)	AT	BE	CZ	DE	FR	HR	HU	NL	PL	RO	SI	SK
CCGT	573	935	170	4340	1588	112	507	2486	529	277	105	359
Coal	0	0	1267	17942	1760	217	42	4061	21052	169	0	0
Coal-derived gas	0	305	375	957	422	0	0	0	272	0	0	0
GT/OCGT	3621	5911	1077	27436	10040	710	3208	15714	3341	1754	664	2270
Lignite	0	0	7177	17598	0	0	1164	0	8299	2545	1278	220
Nuclear	0	5936	3936	4121	60782	0	1916	479	0	1300	696	2921
Oil Fast	355	228	0	2699	2475	43	432	0	404	0	48	0
Hydraulic reservoir	6134	1308	1944	10724	13838	1727	28	0	2060	3356	180	934
Hydraulic run of river	5902	186	340	3737	11695	428	33	0	323	2780	1102	720
Solar	3265	6475	2083	63366	14639	140	3300	22590	10643	1185	294	573
Wind	3569	5315	339	65871	21336	981	323	9410	8978	2957	2	3
Biomass Fast	73	69	35	681	123	5	22	60	63	11	0	0
Biomass Slow	693	656	330	6498	1177	51	209	572	596	110	0	0
Waste Fast	109	106	94	556	0	0	39	642	0	0	29	0

E. Input data time series

This appendix describes the time-series input data used in the simulations. The purpose of these data is to introduce temporal variation in demand and renewable generation, which in turn drives dispatch decisions and market outcomes. The time-series inputs represent energy demand and renewable generation.

Demand profiles

The consumption profiles, defined per season and day type (business and weekend), per MTU and bidding zone, are derived from historical data. They are based on selected historical data and are intended to span a range of market situations. They represent neither actual nor forecasted spatial or temporal variation.

The figure below shows demand profiles for the “winter, weekend” case across selected bidding zones.

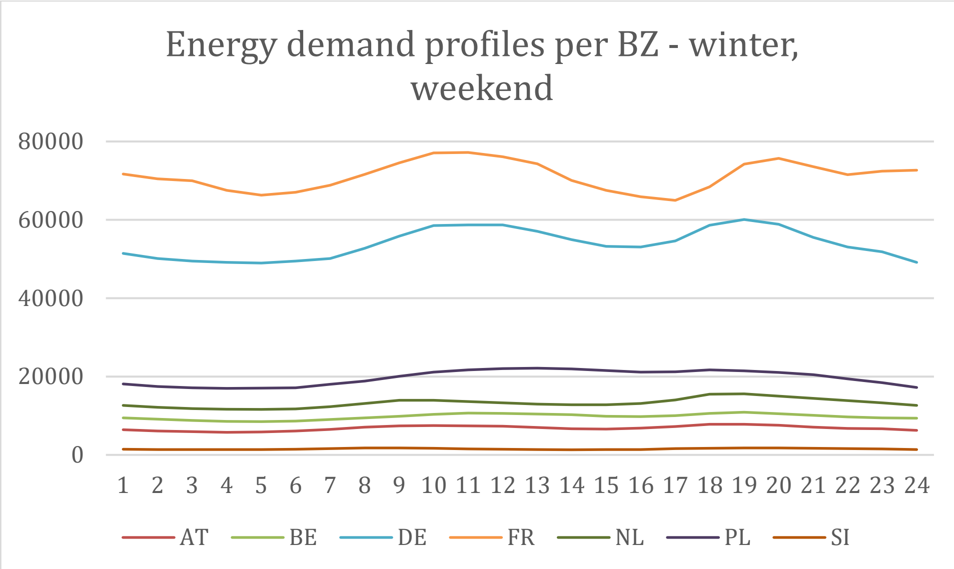


Figure 14 ***Energy demand profiles, winter***

Renewable generation profiles

The production profiles for wind, solar, and run-of-river hydro, defined per MTU and bidding zone for each season, are derived from historical data. They are based on selected historical data and are intended to span a range of market situations. They represent neither actual nor forecasted spatial or temporal variation.

The profiles take values between 0 and 1 and represent the share of installed capacity available in each hour. The figure below shows wind power profiles for the winter season across all bidding zones.

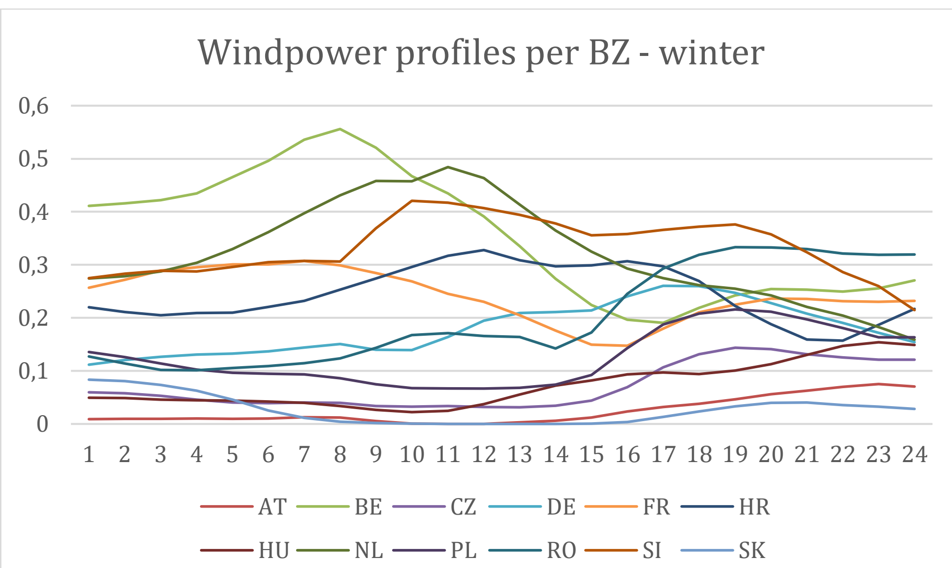


Figure 15 ***Wind power profiles, winter***

F. Balancing capacity requirements

The balancing capacity requirements are constant per bidding zone.

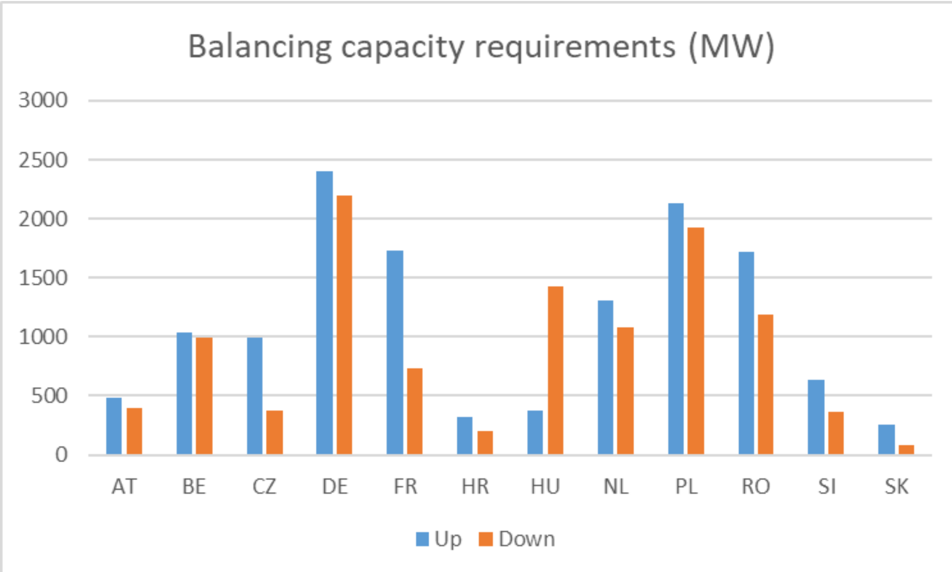


Figure 16 Balancing capacity requirements

G. Summary of Statnett's analysis of the ACER Co-opt Benefit Study

The co-opt benefit study in 2024 published by ACER in 2024 was a comparison of joint and sequential scheduling of energy and balancing capacity under perfect cost information. It assessed the potential welfare impacts of exchange of balancing capacity, in particular whether the exchange is based on sequential markets for balancing capacity and energy or on joint clearing. The study used data covering the CORE region of continental Europe, including 13 countries. The generation data consisted of 618 units representing approximately 594 GW of installed capacity, covering technologies such as nuclear, coal, gas, hydropower, wind and solar. Network data based on actual flow-based transmission-capacity models used in European system operations. Inelastic energy, renewable generation and hydrological data collected from transmission system operators and related data sources. Reserve requirement data for aFRR and mFRR, both upward and downward, for each bidding zone. A full operational year was represented by eight representative day types defined by season and weekday/weekend combinations.

The ACER study found the following reduction of total costs by comparing the joint scheduling to the alternatives:

- 603 MEUR per year (1.14%) compared to no BC exchange (referred to as "status quo").
- 514 MEUR per year (0.97%) compared to sequential scheduling of BC and energy (referred to as "co-optimisation" and "market-based").

Statnett saw room for improvement of ACER's model, and had Optimeering conduct a shadow study replicating the ACER study with minor modifications. Our results were similar to those of the ACER study, with lower potential benefit for joint scheduling of BC and energy:

- 317 MEUR per year (0.60%) compared to sequential scheduling of BC and energy.

The minor modifications we made in the replicated model were in the objective function of the first step of the sequential scheduling – balancing capacity. The original version is shown below.

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

Figure 17 ***Objective function, BC step in sequential clearing, ACER study***

The objective function for the BC scheduling minimizes the sum of

A. Opportunity cost (OC) for upward reserves for inframarginal energy market suppliers.

B. The marginal cost of running at "minimum load plus down-capacity" for all started generators. (C_g is a constant marginal cost of generation)

C. The fixed part FC_g of the linearized total cost of generation for all started generators (according to: $TC(P) = FC_g + C_g * P$)

D. Start-up costs

Element B represents the cost of running extramarginal energy market units for balancing capacity provision, but the objective function includes this cost element of all units, inframarginal and extramarginal alike. This is unfortunate.

Element D, the start-up costs, are considered in full in the BC scheduling, without considering that they might have occurred for the energy market and therefore would be irrelevant to the BC scheduling. Further, the objective function should be able to value reduced start-ups and thus positive and negative values.

In addition to the matters described above, we wanted to define the objective function with power output per generating unit and MT as decision variables, not a mix of power output and balancing capacity provision. The balancing capacity provision is entirely represented as constraints in our version of the model.

Our modified objective function is shown below.

$$\min z = \sum_{g\in G} \sum_{t\in T} \Big(\left(P_g^{MAX} - p_{gt}\right) \cdot OC_g \cdot I_{gt} + \left(MC_{gt} - DAM_t\right) \cdot p_{gt} \cdot \left(1 - I_{gt}\right) + z_{gt} \cdot SC_g \Big) - \sum_{g\in G} SC_g^*$$

Where I_{gt} is binary (1 if inframarginal and 0 if extramarginal).

Figure 18 Objective function, BC step in sequential clearing, Statnett study

Our alternative BC objective function uses energy prices from a joint market clearing (same procedure as the ACER study) and sorts generators into:

- Inframarginal units (energy price > marginal cost)
- Extramarginal units (marginal cost > energy price)

The objective function minimizes the sum of all the following:

- Opportunity costs for inframarginal units:

    - OC × (Pmax − P)
      (where OC is opportunity cost (energy price – marginal cost) per MW
      and P is the power output)

- Profit losses for extramarginal units:
    - P × (marginal cost – energy price)

      (This is typically equal to Pmin or Pmin + down capacity)
- Start-up cost differences relative to a reference energy-only market run.
    - The reference start-up cost for a generator is found as the schedule of a price response to energy market prices from a co-optimization run.

We consider these modifications improvements to the ACER model. However, our main concern regarding the ACER Co-opt Benefit Study is not addressed by these improvements: In order to assess the potential benefits of a market mechanism such as joint scheduling of balancing capacity and energy, the impact of market design choices must also be analyzed. Bid formats impact market efficiency.