Measuring the Benefits of Pricing Transmission Constraints in the European Wholesale Market for Electricity*

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Abstract

We construct a full network model of the European power grid and use it to solve a model that explicitly prices all 6,980 transmission network operating constraints included in the model. We use a detailed dataset of 20,416 generation units in Europe, including 1,014 thermal generation units, and estimate marginal cost of each of these units using data on its thermal efficiency and daily prices of input fossil fuel and European Union carbon allowances for the year 2023. Data on characteristics of the European power grid is used to construct shift factors which govern the power flows between locations, comparable to those used by wholesale market operators in the United States. We use these generation unit marginal cost estimates and transmission network shift factors to solve for the European network-wide minimum operating cost dispatch to meet forecast and realized hourly nodal demands given forecast and realized hourly intermittent renewable generation. This yields potentially 5,324 distinct hourly locational marginal prices (LMPs) and generation unit operating levels at all nodes of the transmission network. We estimate the differences in total variable costs and carbon dioxide emissions between our simulation and observed data from the year 2023 using our marginal cost and emission factor estimates. We find that our simulation yields lower total as-offered costs compares to observed data, while the emission effects are ambiguous. We find that the total variable costs to operate the wholesale market were 3−2 % lower in our nodal pricing compared to actual data and total carbon dioxide emissions were 1−1.5% higher and the output from fossil-fired generators was 2.5 % higher in our simulation compared to actual outcomes.

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1 Introduction

Roth (2007) suggests that "well-functioning markets depend on detailed rules". Roth (2007) provides examples of where seemingly small changes in market rules can transform poorly performing markets into significantly better performing markets. He notes that in different types of markets, widely different mechanisms and institutions have to be established to meet the same basic objectives. The central challenge in designing electricity markets is to find an appropriate level of abstraction from the physical laws that govern the flow of electricity to a well-functioning, sufficiently simple market that aligns the incentives of market participants with the objective of efficiency and cost-minimization. We analyse the European wholesale market of electricity as a high-stakes example of a market where a modest change in market rules has the potential to increase efficiency significantly. We suggest that implementing a two-settlement nodal wholesale market (to set dispatch levels and market prices) that better reflects the constraints involved in operating the power system will increase the efficiency in the European wholesale market. In other words, we argue that the current design of the European market favors simplicity of the market model over fidelity to the operation of the power system at the expense of efficiency.[1]

The European wholesale market for electricity is a financial forward auction where participants enter into commitments to buy or sell quantities of electricity at a specified price. Crucially, this forward auction ignores some constraints that limit the real-time operation of the power system. In particular, the day-ahead auction is cleared based on country-level[2] aggregate supply and demand bid curves, and bids within countries are treated equally. This simplified market clearing ignores transmission constraints that effectively prevent some units within countries/pricing zones from servicing some loads within the same country/pricing zone. This discrepancy implies that transmission system operators must rely on out-of-market interventions to modify market outcomes that cannot be supported with the existing transmission infrastructure (congestion management). To summarize, all units are treated equally in the market clearing, but they cannot necessarily be treated equally in the real-time operation of the power system. The direct cost of congestion management was between 2 and 4 billion euros per year between 2021 and 2024, and there is evidence to suggest indirect costs of similar magnitude (Graf et al. 2020).

The issues associated with simplified pricing models in the context of electricity markets have been recognized since the 1980s (Bohn et al. 1984). A key argument for replacing a simplified market model with one that better represents the constraints that govern the real-time

[1] By efficiency we refer to short-run productive efficiency; i.e., minimizing the cost of generating electricity given the existing infrastructure of generation units and transmission networks.

[2] A small number of countries are divided into pricing zones, but pricing zones mostly correspond to countries

operation of the power system is to eliminate the need for congestion management. There are various mechanisms that can lead congestion management to result in inefficiency[3]. There are two broad types of inefficiency at play: strategic bidding and static misallocation. The necessity of obtaining a physically feasible dispatch for real-time-operation requires TSOs to use out-of-market mechanisms to modify the market outcome. The eventual real-time-operation of the power system might be inefficient due to i) the inflexibility of some units that prevents them from being used in congestion management, ii) imperfect coordination between different TSOs, and iii) a mismatch between minimizing the total variable cost of the dispatch and redispatch costs (static misallocation). Redispatch actions also yield incentives for generators to strategically price themselves into or out of the market in anticipation of the redispatch (strategic bidding). In particular, market participants can modify their bids based on their expectation of congestion management actions. This is essentially a form of arbitrage between the wholesale market and the market used for solving congestion (Hirth & Schlecht 2020). Since this mechanism is predicted to affect the bids submitted to the wholesale market, estimating its effects on market outcomes is not viable without detailed bidding data.

We estimate the potential efficiency improvements from implementing a market model that includes transmission capacity constraints in setting prices and dispatch quantities in the European wholesale market. We allow different prices across different locations within and across countries and current pricing zones that depend on local transmission capacity and generation unit capacity constraints. We construct a market model explicitly based on the nodal pricing (alternatively; locational marginal pricing or LMP) markets currently implemented by most ISOs in the United States. Our market model differs from the current European wholesale market model in one crucial aspect: we clear the market separately for nearly 6000 pricing locations, instead of the 34 currently used in the European market. We use detailed data on local demand and supply conditions, the constraints imposed by existing transmission capacity, supply from intermittent renewable generation resources and marginal costs of fossil-fired generation units (based on technical unit characteristics and daily input costs) to estimate market outcomes for the year 2023 under our alternative market model. We compare our estimated market outcomes to actual outcomes observed in the European wholesale market.

As we model hypothetical efficiency improvements, our article differs significantly from other articles that analyse ex-post efficiency improvements. Due to the scope of this article − as well as the data that we have access to − we model the net effect of all of these mechanisms on the efficiency of the European wholesale market. We estimate both ex-post optimal market outcomes, and market outcomes based on a two-stage model where initial

[3]Both short-run and long-run inefficiency

market-clearing is based on forecasts of demand and intermittent renewables supply, and the real-time operation of the power system is based on realized demand and intermittent renewables supply and a dispatch of fossil-fired generators given by the initial market clearing.

Our estimated aggregate generation mix is similar to the actual observed generation mix, but we find significant and persistent locational price differences within individual countries. We find that the total variable costs to operate the wholesale market is $3-2$ % lower in model compared to actual data and total carbon dioxide emissions are $1-1.5\%$ higher, while the output from fossil-fired generators was 2.5 % higher in our simulation compared to actual outcomes. We estimate that a $3-2$ % reduction in total variable costs is equivalent to $2.8 - 4.2$ billion euros. We furthermore find an 8% increase in the aggregate magnitude of cross-border imports and exports and significant reallocations of generation between countries.

The rest of the article is organized as follows: in section 2, we give a high-level overview of the operation of electricity networks, markets and different pricing models, in particular zonal and nodal pricing. We also describe the current status of the European wholesale market for electricity. In section 3, we describe the mathematical model we use in our analysis and give simplified examples to explain the properties of nodal and zonal pricing. In section 4, we describe the data we use to construct our network model and conduct simulations. In section 5, we present results. In section 6 we summarize and conclude our findings.

2 Institutional background

In this section, we describe the key aspects that make electricity market distinct from the markets for other types of goods. We briefly describe the organization of the European zonal wholesale market for electricity and how transmission system operators (TSOs) address infeasible dispatches with redispatch. We also give an overview of the relevant literature and how our article relates to the existing literature.

Transmission networks are usually described as "transporting" electricity from generation units to consumers ("loads"), but this language is misleading. The power flows in an AC transmission network are jointly determined by nodal net positions and the physical properties of the grid, not by contractual paths between suppliers and customers. TSOs cannot thus route individual transactions through the power grid, and must change the network topology (by manually disabling transmission elements) or nodal net positions to adjust power flows within the grid. Each transmission element has a maximum flow limit (or a thermal limit), and if the power flow through the element exceeds this limit, the transmission element may

be damaged. TSOs ensure that flows in the power grid no not exceed thermal limits to avoid damages and possible cascading failures by monitoring and adjusting nodal positions.[4] This is generally referred to as congestion management. Nodal net positions are given by netting nodal generation and consumption, and in principle TSOs can ensure system stability by adjusting either one. In practice, however, the costs associated with load curtailment (value of lost load; VOLL) are significantly higher than the costs associated with adjusting generation, which implies that TSO primarily rely on the latter to manage grid congestion. The development of demand response and storage technologies may change the volume of loads that can be adjusted to manage grid congestion.

The central challenge in electricity market design is incorporating network and generation unit constraints into market clearing. If the wholesale electricity market ignores some of these constraints, a cost-minimizing day-ahead dispatch is not physically feasible for the real-time operation of the market if some of the ignored constraints are violated. This implies that the final real-time dispatch is as costly or more costly than the unconstrained dispatch. Furthermore, the exact method(s) used in determining the real-time dispatch based on the initial day-ahead dispatch may imply extra costs or inefficiencies.

A *zonal wholesale electricity market* is one where prices and dispatch quantities are calculated by an optimization problem that maximizes some measure of welfare or surplus by setting zonal prices, and includes a set of transmission constraints for the aggregate flows between pricing zones. A pricing zone refers to a large geographical area with a single market-clearing price, and includes a large number of nodes and transmission elements. Transmission constraints for flows within the pricing zone are ignored in the market clearing, which implies that the initial market clearing may be physically infeasible. Physically infeasible allocations arise because zonal market clearing yields the dispatch based only on the zonal merit order, but the flows on transmission elements are determined by the power balances of the nodes in the transmission network within the zone. See 1 for an illustration, and appendix 1 for a simple numerical example. An aggregate cross-zonal constraint also does not account for multiple transmission elements between zones, which may have flows to different directions.

[4]The flow of electricity is not self-governing, which is to say that electricity will flow through a transmission element in excess of its thermal limit if so implied by nodal power balances and the properties of the grid. Damage to one transmission element may imply sudden changes in the flows on other parts of the transmission element, which implies the possibility of cascading damages.

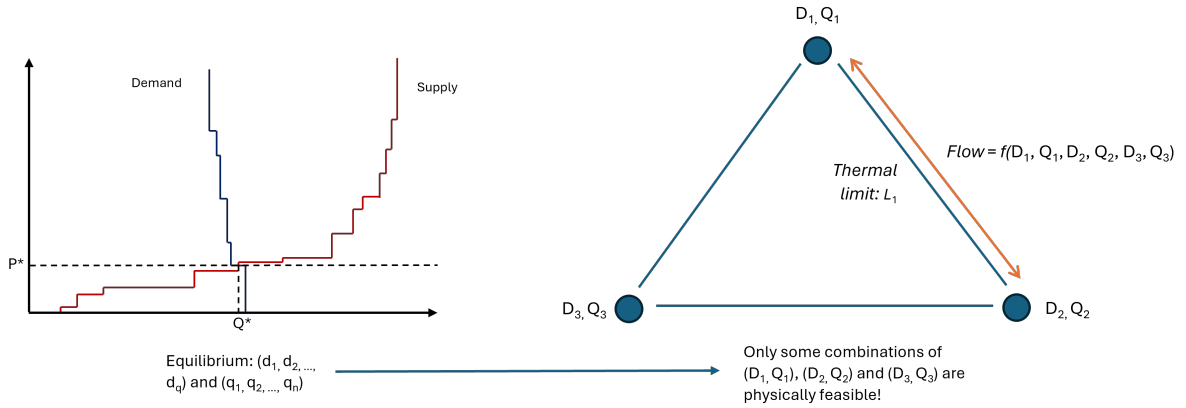


Figure 1: Illustration of why zonal market clearing may imply a physically infeasible allocation. Equilibrium is determined by the intersection of aggregate supply and demand curves, but flows on transmission elements are determined by the spatial allocation of nodal net balances. Only some combinations of $(D_1, Q_1), (D_2, Q_2), (D_3, Q_3)$ are physically feasible, but aggregate (zonal) market treats all possible combinations the same way.

Modifying the day-ahead dispatch to solve physical feasibility in real-time operation is referred to as redispatch. This involves adjusting the output levels of units both up and down until infeasibilities are resolved, preserving aggregate output. This implies that some out-of-the-money bids that were not cleared in the initial market clearing are accepted for real-time operation, and some in-the-money bids that were cleared in the initial market clearing are accepted for real-time operation. The methods of compensating units for redispatch vary across markets, and have important implications for both the short and the long term. Redispatch compensation may be market-based or regulatory. In market-based redispatch, the compensation for up-redispatch is determined by a bid the supplier has submitted (either to the day-ahead market or a specific redispatch market). In regulatory redispatch, the compensation for up-redispatch is determined by the TSO according to its estimate of the marginal cost of the redispatched unit. Down-redispatched bids are generally compensated according to the day-ahead price. The effectively pay-as-bid compensation associated with market-based redispatch may yield perverse incentives for market participants to submit bids that do not reflect their true marginal costs (Hirth & Schlecht 2020). This is one of the two key inefficiencies associated with zonal wholesale markets with large-scale redispatch. See the literature review section for more details on these incentives.

A *nodal market*, or a *locational marginal pricing market* is a wholesale market for electricity in which prices and dispatch quantities are set to accurately reflect the cost of supplying electricity in a particular point in the grid, or a *node*. The key property of nodal pricing is that the dispatch is a cost-minimizing solution to the transmission-constrained economic

dispatch problem. Unlike in zonal markets, the initial market-clearing dispatch is physically feasible, and there is no need for redispatch before real-time operation. The other key property of nodal pricing is that the price at each node reflects the true marginal cost of supplying electricity to that node, which is calculated using the shadow prices of the transmission constraints. In practice, the transmission-constrained economic dispatch problem is solved using a DC power flow model, where key simplifications are used to transform the nonlinear AC power flow problem into a linear DC power flow approximation.

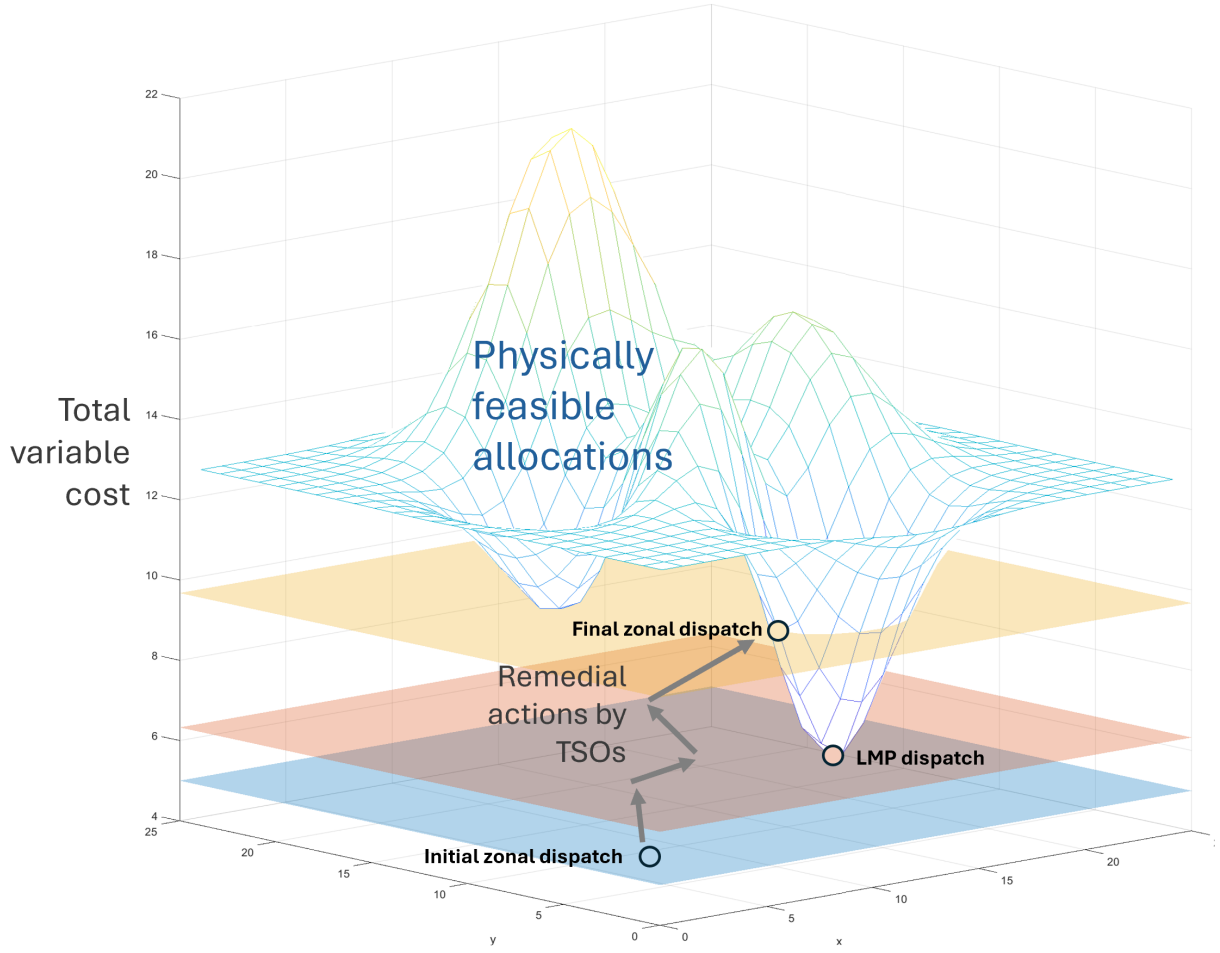


Figure 2: Illustration of the inefficiency associated with zonal pricing. The initial zonal dispatch has a lower total variable cost than the cost-minimizing physically feasible dispatch ("LMP dispatch"), but the initial zonal dispatch is **physically infeasible**. Redispatching ("remedial actions") by TSOs arrive at a physically feasible dispatch, but the final zonal dispatch likely has a higher total variable cost than the LMP dispatch due to inefficiencies associated with redispatch.

A fundamental reality of the operation of electricity markets is that the real-time dispatch will always be physically feasible. In nodal market clearing, this dispatch is the cost-minimizing physically feasible dispatch by construction. In zonal markets, the real-time dispatch differs from the initial market-clearing dispatch if some transmission constraints are violated by the market-clearing dispatch. Due to limited information, generation unit flexibility and coordination between different TSOs (static inefficiency; see 2) and incentives for market participants to submit bids that differ from their true marginal costs, it is unlikely that the real-time dispatch in zonal markets coincides with the cost-minimizing dispatch. Our article quantifies this difference in total variable costs in Europe for the year 2023.

2.1 The European market for electricity

The European wholesale market for electricity operates under a zonal pricing structure, where most countries correspond to one pricing zone; some countries are divided into subnational pricing zones. The day-ahead price is set by pooling all demand and supply bids in a single pricing zone and finding the surplus-maximizing[5] equilibrium given a set of transmission constraints between pricing zones. These transmission constraints may be static (Available transfer capacity; ATC), or depend in some way on intrazonal congestion (Flow-based market coupling; FBMC) (Van den Bergh et al. (2016), for more detailed analysis, see Kristiansen (2020) and Schönheit et al. (2021)). Bohn et al. (1984) show that the optimal pricing of electricity is disaggregated across space and time. While the European wholesale market employs 15-minute pricing and pricing zones, it falls sort of the key condition that the prices should reflect the underlying physical constraints imposed by the power grid.

Similar to many American regional electricity markets, the European electricity market restructuring started from liberalization of local monopolies and country-level zonal pricing. However, more robust transmission networks and a relative lack of congestion created little pressure to adopt nodal pricing in Europe compared to the United States, where high levels of congestion created pressure to reorganize the market to minimize the efficiency losses associated with large-scale redispatch. (Wolak 2021). An important aspect of the European market liberalization process is the creation of a centralized wholesale electricity market. While day-ahead prices and quantities are determined by a central algorithm, national (and local) TSOs have responsibility for solving physical infeasibilities after the day-ahead market clearing. National TSOs in Europe employ a wide variety of different strategies to manage congestion within pricing zones (Bindu et al. (2024)), and redispatch with limited coordination. This lack of coordination (along with limited information and flexibility of generation

[5]The European wholesale market algorithm, the EUPHEMIA, maximizes the sum of consumer and producer surplus and congestion rents (*EUPHEMIA Public Description: Single Price Coupling Algorithm* 2024)

units) in redispatch is a key reason for why European real-time dispatches are unlikely to coincide with the actual variable cost minimizing dispatch (allocative inefficiency).

Like most wholesale markets for electricity, the European wholesale market involves multiple mechanisms that operate over different periods of time. The four key markets and mechanisms in the European wholesale market are:

- Day-ahead market
- Intraday market
- Balancing/redispatch (market-based or regulatory)
- Ancillary services markets

In this article, we focus on the day-ahead market and redispatch. The sequence of these two market mechanisms in the European wholesale market is as follows: the day-ahead market is cleared a day before the corresponding the real-time operation. TSOs then calculate the intrazonal flows implied by the market-clearing spatial allocation of generation and demand, and redispatch to solve any potential infeasibilities. A detailed description of the microstructure of the European wholesale market is beyond the scope of this article, but a concise explanation is that all of the above market mechanisms are essentially financial constructs that create incentives for market paricipants to align their behaviour with the TSOs' objectives of maintaining a well-functioning power system. We give a more detailed overview of the sequence of different markets and mechanisms in the appendix.

The European wholesale market uses a complex algorithm, EUPHEMIA, to clear the market (*EUPHEMIA Public Description: Single Price Coupling Algorithm* (2024)). The algorithm maximizes the sum of consumer surplus, producer surplus and congestion rents (i.e. economic surplus). The option to submit complex bids that have specific acceptance conditions (beyond price) makes this non-linear optimization instead of a linear optimization problem. The solution produced by EUPHEMIA is a set of aggregate zonal supply quantities, prices, and cross-zonal flows. The solution strictly enforces the zonal merit order for simple bids.[6]. All TSOs that participate in EUPHEMIA have adopted flow-based market coupling (FBMC) to determine intrazonal flow constraints. In FBMC, the solution domain is determined based on forecast intrazonal congestion, but this only allows intrazonal transmission constraints to enter the optimization problem as inputs to a function that determines an aggregate cross-zonal transmission constraint. This can alleviate intrazonal congestion,

[6]But not for complex bids, which may be paradoxically rejected while all their associated acceptance conditions are met given the EUPHEMIA solution (but not paradoxically accepted)

but falls critically short of the electricity pricing efficiency conditions derived by Bohn et al. (1984).

As a zonal market-clearing algorithm, EUPHEMIA ignores intrazonal transmission constraints in the market clearing. One of the properties of EUPHEMIA is that all in-the-money bids are cleared (i.e., the algorithm enforces the zonal merit order). These bids may be associated with generation or consumption in any part of the pricing zone, but they are all treated equally. However, only a subset of all possible spatial distributions of generation and consumption are physically feasible. EUPHEMIA cannot address this issue by definition, since including intrazonal transmission constraints in the market-clearing algorithm is not compatible with enforcing the zonal merit order. The solution created by EUPHEMIA is cost-minimizing only in a "zonal copper plate sense"; i.e., if there is unlimited transmission capacity within zones. The zonal merit order and limited intrazonal transmission capacity create the need for congestion management/redispatch. In the next section, we will argue why it is unlikely that the eventual real-time dispatch in the European wholesale market coincides with the true cost-minimizing dispatch.

2.2 Congestion management in the European market for electricity

The direct cost of congestion management in the European Union was 4.3 billion euros in the year 2023 (for the Cooperation of Energy Regulators 2024), representing an increasing trend (3). The volume of all remedial actions related to congestion management was approximately 57 TWh, which is equivalent to about 2.5% of the total volume of electricity produced during this year. While these numbers may sound relatively meager, the indirect costs associated with congestion management strategies (i.e., changes in generator bidding behaviour as a response to the INC-DEC game) are likely much larger. In particular, Graf et al. (2020) suggest that when accounting for the changes in bidding incentives implied by congestion management, the total economic cost of redispatch represented about 15% of the real-time demand valued at the day-ahead market price in the Italian wholesale market. As the authors point out, these costs are likely higher in other European countries that incorporate less spatial granularity of pricing than the Italian market.

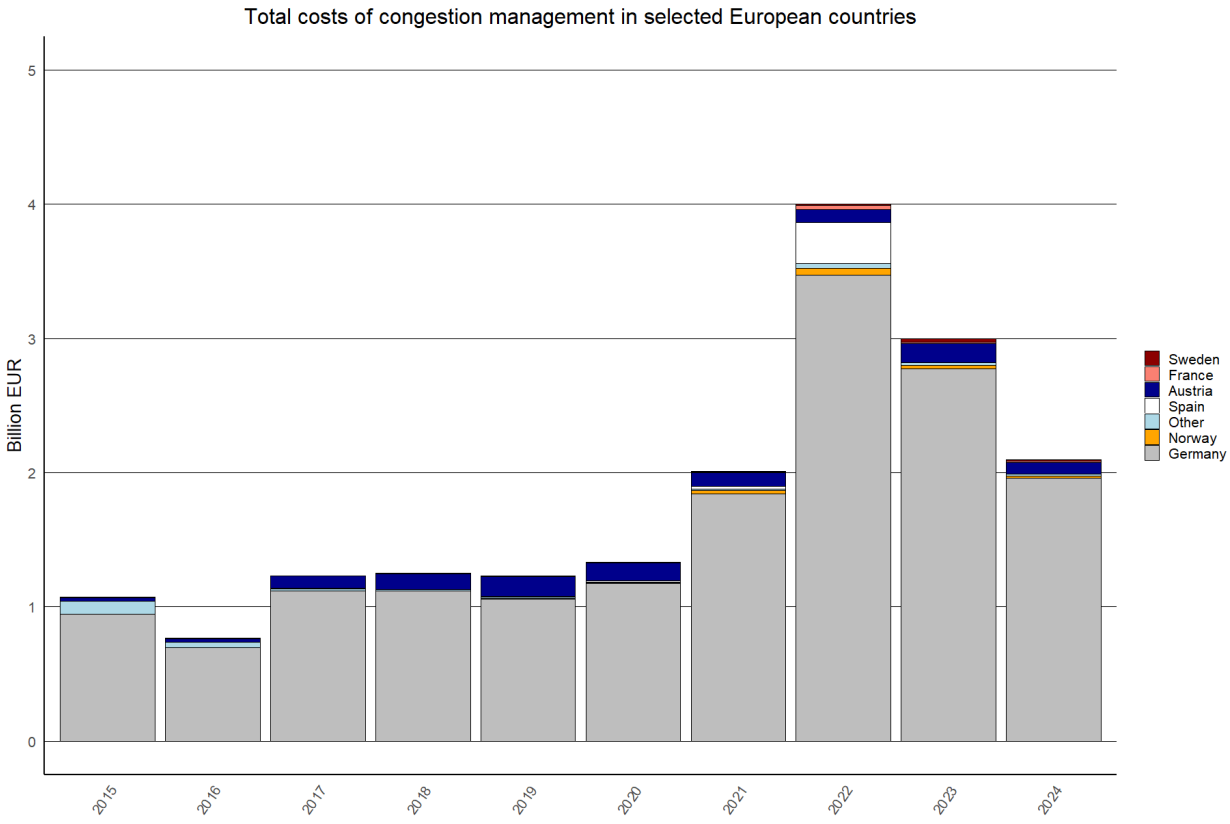


Figure 3: The total direct costs (redispatch costs + countertrading costs) of congestion management in the European market for electricity from 2015 to 2023 per country. Data: ENTSO-E Transparency platform: costs of congestion management (*ENTSO-E Transparency Platform: Costs of Congestion Management* (2025))

While a detailed analysis of all congestion management strategies currently employed in the European market for electricity is outside the scope of this article, we make some general observations. The key aspect of congestion management is whether it can be considered market-based or regulatory (where appropriate levels of compensation are determined by the TSO). Most TSOs in Southern, Western and Northern Europe [7] employ market-based congestion management strategies, with the exception of Germany and France (Zahler et al. (2023)). Most central/eastern European employ congestion management strategies that can be considered regulatory congestion management strategies, although many of these TSOs have not publicly disclosed their congestion management strategies. In the majority of countries that participate in the European market for electricity, the volume of remedial actions

[7] In particular: Finland, Sweden, Norway, the Netherlands, Spain, the United Kingdom and Italy

related to congestion management represent a very small share of total electricity demand (between 0 and 1 %). The key exceptions to this are Germany, Spain and Poland, where the volume of remedial actions as a share of total demand are between 5 and 7 % (for the Cooperation of Energy Regulators (2024)). Two of these three countries employ regulatory congestion management strategies, although there is no evidence to suggest any causal effects.

The key concern related to market-based redispatch is known as "INC-DEC gaming" (Hirth & Schlecht 2020). This concept refers to a bidding strategy where market participants modify their bids based on their perceived likelihood of being targeted by redispatch measures. In particular, Hirth & Schlecht (2020) show that market based redispatch 1) creates bidding incentives that aggravate transmission congestion, 2) creates incentives for generation and load unit investments that profit from the INC-DEC arbitrage and 3) implies redispatch prices that resemble nodal prices. We will give a more detailed overview of the inc-dec game in the literature review section.

While the distinction between market-based and regulatory congestion management strategies is of crucial interest to ensuring adequate compensation for the owners of generation assets and fair competition between market participants, this distinction is only of partial interest to our analysis.[8]. In our quantitative analysis, we do not attempt to model strategic INC-DEC behaviour, nor do we model static misallocation as a result of imperfect information, cross-TSO coordination, or generation unit flexibility. Our nodal pricing model is a benchmark that quantifies the net effect of static misallocation and INC-DEC behaviour on system-wide total variable costs.

The fact that large-scale redispatch may in practice imply generation unit compensation that somewhat resemble locational marginal prices is rarely discussed. This is caused by the fact that units in import-constrained nodes have a relatively high likelihood of being DEC-ed, which yields incentives for these units to bid above their true marginal cost, and units in export-constrained nodes have a relatively high likelihood of being DEC-ed, which yields incentives for these units to bid below their true marginal cost (to be able to buy back the energy they sold in the initial market clearing). However, the remunerations market participants receive from redispatch are not reflected in zonal prices, and there is no mechanism to ensure that all market participants in the same location are treated equally. In practice, the INC-DEC-remunerations are also not publicly available information, and do not thus create a similar price signal as true locational marginal prices.

[8]Market-based redispatch can be achieved through separate redispatch and capacity markets, or simply on the day-ahead or intraday market. The redispatch price obtained by a market participant called to adjust their output after the primary market clears is equal to the bid they submitted to the redispatch/balancing market or alternatively the day-ahead or intraday market, depending on which market is used in the redispatch.

2.3 Literature review

Electricity market design includes many dimensions, but the key element is arguably the spatial granularity of pricing. While all electricity markets can be thought to fall on a continuum of different levels of spatial granularity of terms of wholesale pricing[9], the literature generally treats zonal pricing and nodal pricing as two distinct categories. The European wholesale market includes very little spatial granularity while most US markets employ very high levels of granularity; various markets globally fall somewhere between these two end points. As outlined before, there are broadly two sources of inefficiency in the European wholesale market: static misallocation and strategic bidding.

There is a body of literature that analyzes the optimal pricing of electricity; we refer to Bohn et al. (1984) for the general optimality result. The potential efficiency and welfare losses associated with zonal pricing have been recognized from the start of electricity market restructuring (Bjørndal & Jørnsten 2001, Stoft 1997, Walton & Tabors 1996), but they have been considered a reasonable trade-off to constructing a simplified and workable day-ahead market. Increasing transmission congestion and redispatch costs, particularly in Europe, have forced regulators to rethink this trade-off. However, European stakeholders are generally skeptical of discarding the current model of simplified day-ahead market clearing (Eicke & Schittekatte 2022). In particular, Eicke & Schittekatte (2022) survey various arguments against the nodal pricing model by European stakeholders (such as local market power, lack of market liquidity, complexity, investment risk) − as well as methods used to mitigate these issues in US markets − and conclude that these arguments do not constitute a credible reason to reject nodal pricing.

A key concern related to nodal pricing is that greater spatial granularity ("smaller markets") yields more opportunities to exercise market power. Harvey & Hogan (2000) show that this argument is based on an erroneous conflation of administrative pricing zones with the physical transmission grid. If a supplier has locational market power − its output is pivotal due to physical transmission constraints − it can exercise market power in any market-based market-clearing−redispatch regime, either through the day-ahead market of the redispatch market. This follows from the fact that the administrative aggregation of nodes into pricing zones does not alter the operation of the power grid. Harvey & Hogan (2000) furthermore argue that under some conditions, zonal pricing can actually underperform nodal pricing in competitiveness. In particular, the authors argue that zonal pricing can create opportunities to exercise market power that would not exist in a *ceteris paribus* nodal pricing market, as zonal pricing creates administrative constraints that might not exist in the real-time operation of the power grid. The opposite is generally never true.

[9]How many physical feasibility constraint are considered and priced in the wholesale market clearing

The static allocative inefficiency associated with a zonal market with large-scale redispatch is the distance of the zonal real-time dispatch from the optimal (nodal) benchmark dispatch. In principle, it is not impossible for TSOs to implement the optimal dispatch with zonal pricing and redispatch. However, various mechanisms cause allocative inefficiency in zonal pricing markets with redispatch. Grimm et al. (2022) show that market-based redispatch implies a mismatch between the TSOs objective of redispatch cost minimization and welfare maximization. In the European context, a lack of coordination between national TSOs implies further inefficiency (Weber et al. 2022). Other possible mechanisms include imperfect information on the TSO side, as well as generation asset flexibility issues. In the European context, the latter mechanism may arise from the fact that inflexible units (scheduled according to day-ahead market clearing) may be unavailable for redispatch that occurs shortly before real-time operation. These two mechanisms have not been systematically studied in the literature.

Hirth & Schlecht (2020) analyze INC-DEC gaming, a type of strategic bidding that may occur in a zonal market with large-scale market-based redispatch. This strategy involves certain market participants adjusting their day-ahead bids based on their perceived likelihood of redispatch actions. In particular, generators in import-constrained nodes may strategically increase the prices of their day-ahead bids in order to price themselves out of the day-ahead market, anticipating a greater price in the redispatch market. Generators in export-constrained nodes may strategically decrease the prices of their day-ahead bids in order to price themselves into the day-ahead market, anticipating an opportunity to buy back the electricity at a lower price in the redispatch market. Zonal markets with large-scale market-based redispatch thus generate opportunities for market participants to arbitrage between the day-ahead price (that does not price intrazonal transmission constraints) and the redispatch price (that prices intrazonal transmission constraints). The authors show that, INC-DEC-gaming increases congestion, producer rents and raises redispatch costs in the short run, and creates perverse investment incentives to invest in generation in export-constrained nodes and loads in import-constrained nodes in the long run. Notably, the price arbitrage opportunity that leads to INC-DEC-gaming is based on locational price differences on the redispatch market. These price differences − necessary for market-based redispatch in a zonal pricing market − are functionally similar to nodal day-ahead prices, but they are less transparent and are not available to all market participants in the same node equally.

Our article presents a competitive benchmark for a European nodal pricing market where all major transmission network and unit capacity constraints are priced. We furthermore use data of actual market outcomes from the current European zonal market to quantify the net effect of the two types of inefficiencies associated with the current European wholesale market. Our article belongs to a wider body of literature that attempt to quantify the same net effect, usually on the level of countries; Karhinen & Huuki (2020) (Finland), Ding & Fuller

(2005) (Italy), Green (2007) (England) Leuthold et al. (2007) (Germany) or larger groups of countries; Neuhoff & Hobbs (2013) (Central Europe). To our knowledge, no previous article has attempted to quantify a competitive nodal market benchmark for the entire European wholesale market. Furthermore, some of the aforementioned articles have used simplified models of the power grid, which implies that the results may themselves ignore a large share of transmission constraints (that should ostensibly be priced in a nodal benchmark model). The European Network of Transmission System Operators (ENTSO-E) (*Report on the Locational Marginal Pricing Study of the Bidding Zone Review Process* 2022) has published a technical study of the potential outcomes of a nodal pricing market in Europe, but this analysis does not attempt to quantify the net effect of the two inefficiencies associated with the current European wholesale market.

Previous literature that attempts to quantify the efficiency gains associated with a transition from a nodal pricing market to a zonal pricing market has found the direct effect to be in the magnitude of $1-4\%$ of total operating costs (Wolak (2011), Triolo & Wolak (2022), Neuhoff & Hobbs (2013), Zarnikau et al. (2014) and Aravena & Papavasiliou (2017)). In particular, Wolak (2011) and Triolo & Wolak (2022) has used data from markets that have implemented such a transition, while other literature relies on simulation-based methods. Graf et al. (2020) quantify the effects of the INC-DEC-game using data from individual bids in the Italian market for electricity. In particular, they find that a 0.1-unit change in the probability of having its day-ahead schedule changed will lead suppliers by 5 or 6 EUR/MWh (for schedule increases and decreases respectively). The authors estimate that the total economic redispatch costs (accounting for all INC and DEC payments to market participants) is 15 % relative to real-time demand valued at the day-ahead market price. The authors furthermore suggest that these costs may be even higher in other European countries that implement less spatial granularity in pricing compared to the Italian market.

3 Market-clearing model

In this section, we introduce our model of nodal pricing, and analyze the potential issues associated with zonal pricing with redispatch. To introduce the concept of nodal pricing, we introduce a very simple three-node model and illustrate the properties of nodal pricing. To introduce the key issues associated with zonal pricing with redispatch, we introduce a simple six-node model with two system operators who redispatch independently in their segment of the power grid. We model zonal pricing using market-clearing and redispatch rules that reflect the operation of the European wholesale electricity market. In the first stage of zonal market clearing, the market is cleared ignoring all intrazonal transmission constraints and only considering cross-zonal transmission constraints. In the second step, the TSOs observe

the first-stage market-clearing dispatch and the implied power flows and then redispatch in an independent sequential redispatch process until all line flows are physically feasible. We show that higher distances between the starting point of the redispatch process and the actual as-offered-cost-minimizing dispatch is associated with higher redispatch costs and higher total variable costs of the final dispatch.

3.1 Nodal pricing in a simplified network

We choose a three-node network over a two-node system to include a loop flow, which is a factor that significantly complicates the delivery of electricity from producers to loads in real-world power systems. Our three-node system is shown in figure 4. The system includes two generation nodes and one load node. The nodes are connected together in a triangular fashion with identical transmission lines that have a maximum thermal capacity of 400 MWh each. Both generation nodes have 750 MWh of generation capacity. The marginal cost of generation capacity in node 1 is 50 €/MWh and the marginal cost of generation capacity in node 2 is 100 €/MWh. We solve an economic dispatch model where the objective is to supply x MWh of electricity to the load node with minimum cost while not violating any transmission constraints (physical feasibility). We then determine nodal prices using the shift factor matrix and the shadow prices of the thermal capacity constraints. We recall that the nodal price is equal to the change in the value of the optimized value of the objective function as a response to a one-unit increase in demand in a node.

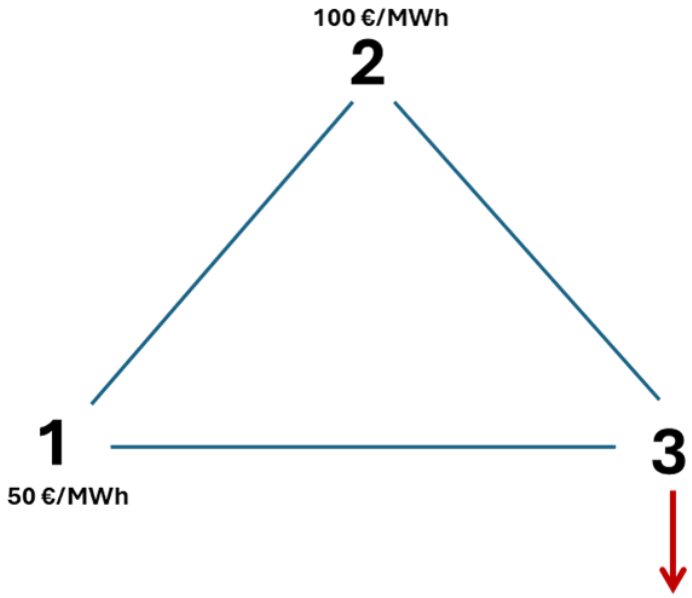


Figure 4: Schematic of the three-node system. Node 1 has cheap generation capacity (50 €/MWh), node 2 has expensive generation capacity (100 €/MWh) and node 3 is the load node.

Figure 5: Nodal prices and load in the 6-node system. The transmission constraint between nodes 3 and 1 becomes binding at $D = 600$, and nodal prices diverge. Note also that most nodal prices are linear combinations of the marginal costs of different generators, as the system now has three loop flows that have to be accounted for when dispatching. Increasing load in one node may require more complex changes in the outputs in different nodes than in the 3-node system.

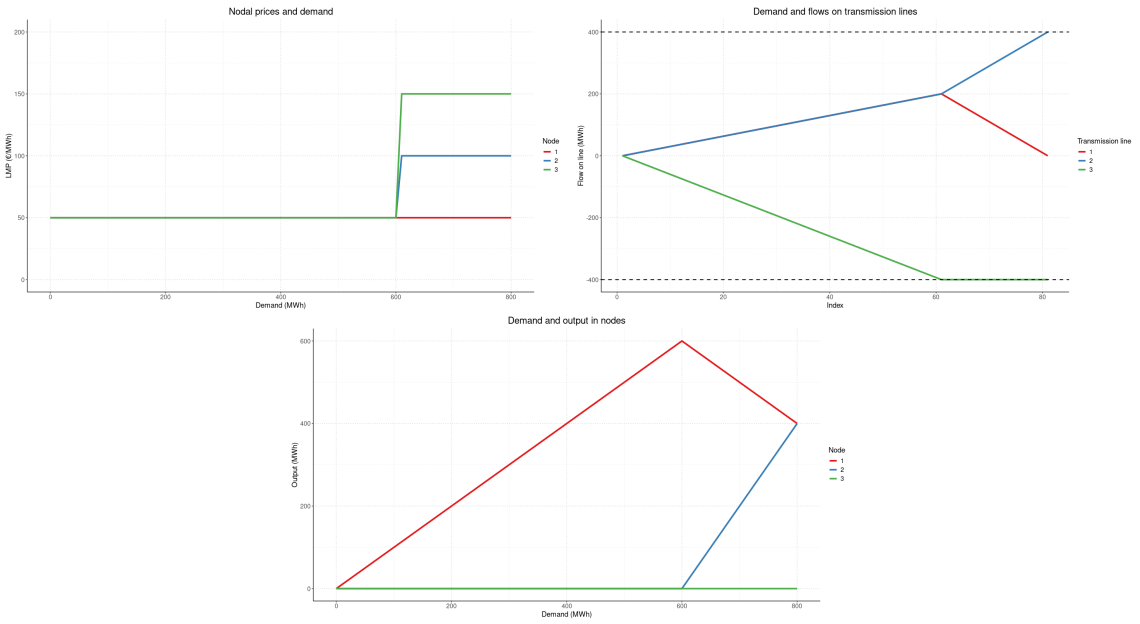


Figure 6: Nodal prices (LMPs), nodal outputs and line flows for different levels of load in the 3-node system.

This example illustrates the key properties of nodal pricing. All nodal prices are equal when load is less than 600 MWh, but for loads larger than this, one of the transmission constraints is binding (for the optimal economic dispatch), and nodal prices diverge. The binding transmission constraint implies that the nodal price in the load node is 150 €/MWh when loads exceed 600 MW. In order to compensate a one-unit increase in load while keeping the flow between nodes 3 and 1 within the physical feasibility constraint, output in node 2 (marginal cost 100 €/MWh) must increase by two units and output in node 1 (marginal cost 50 €/MWh) must decrease by one unit. Generation unit capacity constraints are not binding for any level of load in this simplified model. The shadow prices (and thus nodal prices) are linear combinations of the marginal costs of the marginal units in all nodes, which may result in nodal prices that exceed the marginal costs of the most expensive marginal generators. Our economic dispatch model of the European power system does not fundamentally differ from the basic logic behind this three-node model, although it includes thousands of linear constraints related to the capacity of transmission lines, generation units and generation gradients.

3.2 Zonal pricing with redispatch in a simplified network

We then analyze a six-node network that is constructed by connecting together two identical three-node networks. We use this example to introduce our argument that a lack of coordination in redispatching can lead to non-optimal outcomes. We consider the optimal outcome to be the solution to the simple economic dispatch problem, and study how the initial zonal market outcome converges (or rather, how it most likely will not converge) to the optimal outcome under the assumption with two TSOs that redispatch without coordination. In the interest of brevity, we include most of the analysis on TSO revenues in the appendix. We start by reporting the optimal dispatch in the six-node network (this is equal to the outcome generated by the economic dispatch problem, or nodal market clearing), and then comparing this outcome to the outcomes generated by zonal market clearing with redispatch under various assumptions. We model redispatch as a two-stage algorithm in the following way: The market is cleared based on the merit order of generation units while imposing cross-zonal transmission constraints (i.e., the transmission capacity constraints of the lines connecting nodes 3 and 5 and 2 and 4 respectively) and ignoring all other transmission capacity constraints (first stage). Since most transmission constraints are ignored in the first stage, the resulting dispatch can be physically infeasible and redispatch is required before the actual (real-time) operation of the power system. We model the redispatch process as a sequential game in the following way: one of the two TSOs (chosen arbitrarily) observes the initial dispatch and the implied line flows. If some transmission constraints within the TSOs control area are violated, the TSO redispatches generation between its generation units until no transmission constraint within its control area (or the cross-zonal transmission constraints) are violated. After this, the other TSO observes the new dispatch and redispatches until no transmission constraint within its control area (or the cross-zonal transmission constraints) are violated. The TSOs continue this sequential process until no transmission constraints are violated. Changing the spatial allocation of generation in one TSOs control area affects line flows in the other TSOs control area due to loop flows, which implies that the redispatch process can take more than two steps.[10] We furthermore assume that the TSOs compensate generators for each unit that is redispatched-up; i.e., the TSOs pay the market-clearing price for each unit of electricity that a generator produces on top of the initial zonal dispatch. We assume that the TSOs select the redispatch that results in the least costs on each step of the sequential redispatch process. We implicitly assume that the redispatch process preserves the initial zonal power balance, i.e., redispatching can only occur within a control area. We analyze the economic dispatch problems for different levels of load from 0 to 800 MWh. For ease of analyzing the results, both load nodes have the same level of load. The largest total

[10] Indeed, the redispatch process does not necessarily converge to a physically feasible dispatch. This can be either due to the fact that a physically feasible dispatch does not exist for the given zonal power balances, or since the sequential process simply fails to converge to a physically feasible dispatch even though such may exist. We forgo a detailed analysis of the convergence of this sequential process.

load in the system is thus 1600 MWh, and we analyze the sequential redispatch problem for this level of load.

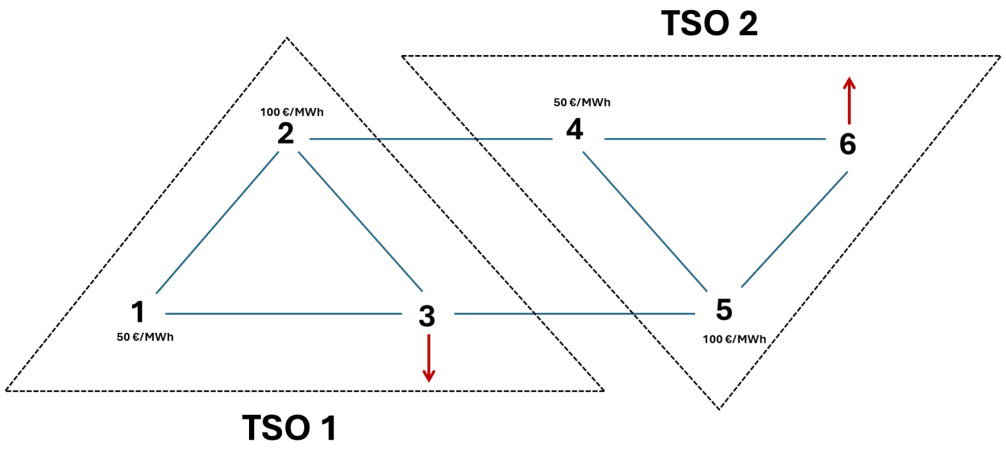


Figure 7: Schematic of the six-node system. Nodes 1 and 4 have cheap generation capacity (50 €/MWh), nodes 2 and 5 have expensive generation capacity (100 €/MWh) and nodes 3 and 6 are the load nodes. We assume that the network is operated by two TSOs which ensure that the flows of transmission lines within their own control area (marked by dashed lines) are physically feasible in the analysis of zonal market clearing with redispatch. The division of the network into two control areas is irrelevant for nodal market clearing, but relevant to the analysis of redispatch with imperfect coordination.

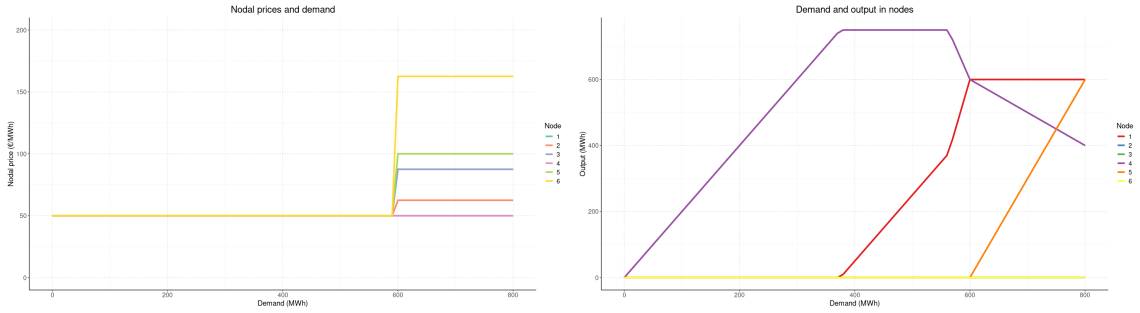


Figure 8: Nodal prices (LMPs), nodal outputs and line flows for different levels of load in the 6-node system.

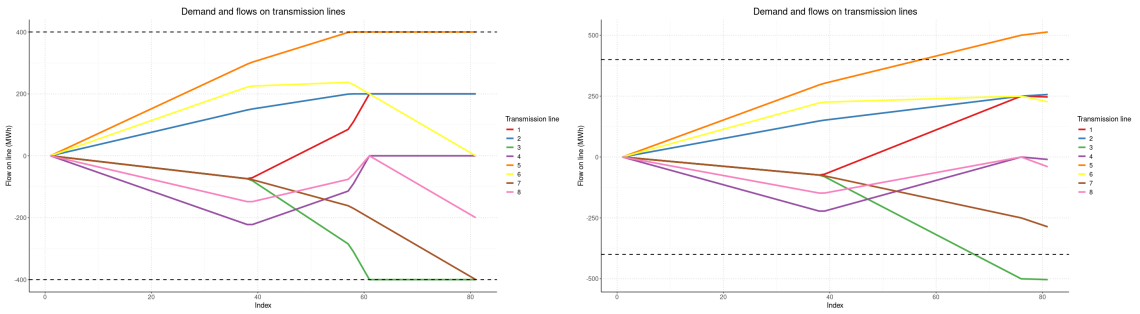


Figure 9: Flows on transmission lines for different values of load (x-axis) under nodal pricing (left) and the initial dispatch for zonal pricing before redispatch (right). The dashed line marks the 400 MWh transmission line capacity constraint.

We see from figures 9 and 8 that for loads larger than 580 MWh, one of the transmission constraints in the nodal pricing problem becomes binding, and nodal prices diverge. However, for the zonal pricing problem, loads larger than 580 MWh imply that one or several of the intrazonal transmission constraints are violated. This occurs since these transmission constraints do not enter into the linear optimization problem. In what follows, we will briefly analyze our model of sequential redispatch and discuss the potential inefficiencies associated with it.

The cost-minimizing initial dispatch in a zonal market with redispatch for $D_1 = D_2 = 800$ is the following: $Q = (c1 = 750, e1 = 0, c2 = 750, e2 = 100)$. In TSO 2's control area, the expensive unit is the marginal unit, and therefore the corresponding zonal price is 100 €/MWh. In TSO 2's control area, the cheap unit is technically the marginal unit, but since this unit is at its capacity, a one-unit increase in load must be satisfied by increasing imports or generation by the expensive unit. The zonal price in TSO 1's control area is therefore also 100 €/MWh. $Q = (c1 = 750, e1 = 100, c2 = 750, e2 = 0)$ is also a cost-minimizing dispatch, but we will analyze the former for the interest of brevity. We report the steps of the sequential redispatch process in the tables below. We note that the redispatch process converges on a different outcome depending on which TSO starts the redispatch process:

TSO 1 starts the redispatch process:

Redispatch step	c1	e1	c2	e2	total variable cost (€)	redispatch cost (€)
Initial dispatch	750	0	750	100	85,000	–
2	500	250	750	100	97,500	25,000
3	500	250	313	537	119,350	43,700

We also analyze what happens when the sequential redispatch starts from TSO 2:

Redispatch step	c1	e1	c2	e2	total variable cost (€)	redispatch cost (€)
Initial dispatch	750	0	750	100	85,000	–
2	750	0	344	506	105,300	40,600
3	572	178	344	506	114,200	17,800
4	572	178	322	528	115,300	2,200

We find that this sequential process is unlikely to converge on the actual cost-minimizing physically feasible dispatch given a set of zonal power balances. We find that there are a total of $639,101$ possible dispatches given the zonal power balances and $D_1 = D_2 = 800$, but out of these only $21,695$ are physically feasible (about 3.4%). The total variable cost of the least expensive physically feasible dispatch of this set is $115,050$ € and the total variable cost of the most expensive dispatch is $149,300$ − a considerable difference. While the difference in costs of the least expensive dispatch and our sequentially generated dispatch (starting from TSO 2) is only 250 € (a difference of about 0.2%), our simplified model also highlights the fact that although the redispatch process may end very close to the variable-cost minimizing dispatch, the TSOs must incur considerable costs during the redispatch process. Regardless oh which TSO starts the sequential redispatch process, the total redispatch costs are over 50 % compared to the total variable costs.

The key sources of inefficiency in our model of sequential redispatch are i) the lack of coordination between the TSOs and the TSOs objective to minimize the redispatch cost at every step, and ii) the assumption that TSOs redispatch for a given set of zonal power balances (imports/exports). Both of these assumptions generally reflect the current state of congestion management in the European wholesale market. We observe that while the total variable cost of the dispatch is quite close to the benchmark efficient dispatch regardless of which TSO starts the sequential process, the redispatch costs are significant compared to the total variable cost. A more detailed analysis of generator profits also reveal perverse incentives to invest in generator only to benefit from redispatch (the inc-dec-game). See appendix 6 for a more detailed analysis of the sequential redispatch process with two TSOs.

Finally, we simulate our sequential redispatch process for a number of randomly selected initial positions. We find that the further the initial position is from the actual variable cost-minimizing dispatch, the larger are the total variable costs of the final dispatch that the sequential redispatch process converges to. We also find a positive association with the distance between the starting point of the redispatch process and the actual variable cost-minimizing dispatch and the redispatch costs, although there is a significant amount of noise in this association. These results imply that the starting point of the redispatch process matter not only for the redispatch costs, but they also influence where the redispatch process converges to.

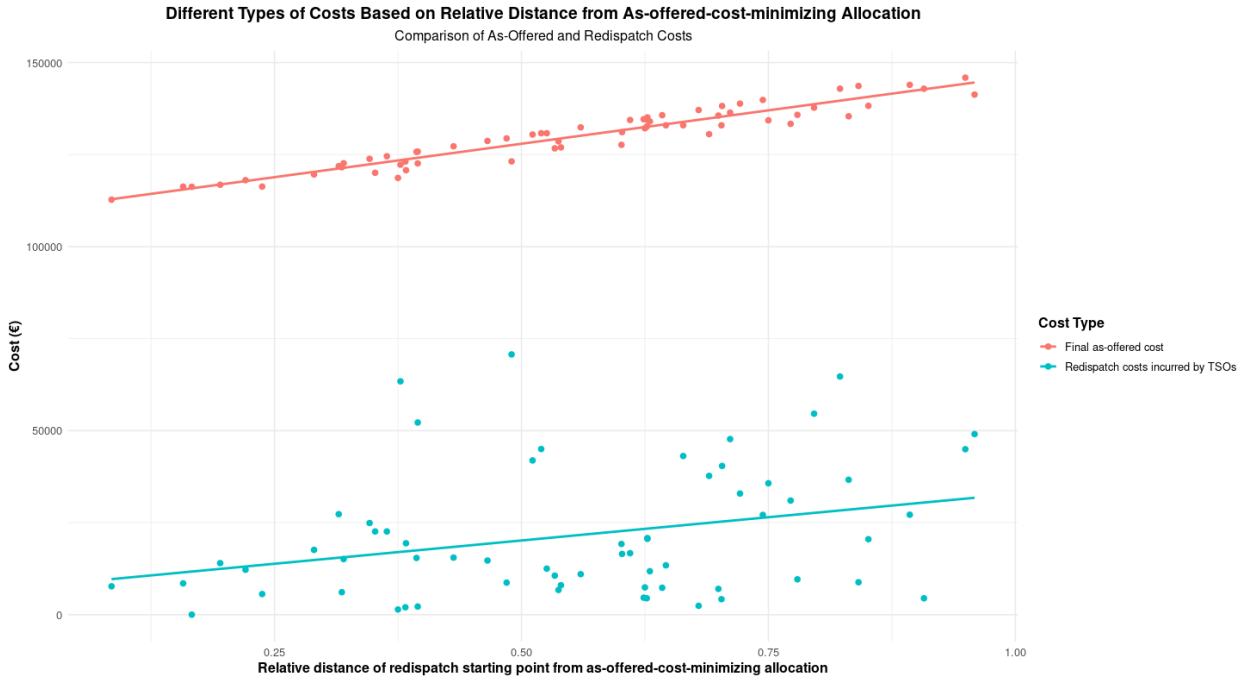


Figure 10: Scatterplot: outcomes of the sequential dispatch process and the relative distance between the initial dispatch and the optimal cost-minimizing dispatch. We calculate the relative distance as a simple euclidean distance between the two vectors of generation. More distance between the optimal dispatch and the initial starting point is associated with higher redispatch costs and higher total variable costs of the final dispatch.

3.3 An economic dispatch model of the European power system

In this section, we give a detailed description of our economic dispatch model of the European power system. While our market-clearing model is conceptually identical to the simplified models presented earlier in this section, the large amount of different types of generators and the number of transmission constraints force us to make various assumptions that we will detail in this section. We solve an economic dispatch problem using actual data on the European transmission system, generation units, daily input prices (fuel and emission allowance prices), hourly demand condition, hourly country-level data on the output from intermittent renewables and plant-level data on the output of nuclear generation units. We let prices vary across all nodes of the transmission system, which yields potentially 6,980 distinct nodal prices. We solve the economic dispatch problem simultaneously for all 24 hours of a day, following the market-clearing in real-world wholesale electricity markets. We make the following assumptions:

1. Firms bid all available capacity at its marginal cost.

2. Wind, solar and run-of-the-river hydropower generation units are assigned a marginal cost. The capacity of these units is adjusted so that the sum of the capacities of the generation units of intermittent generation technology k in country j equals the actual hourly output from technology k in country j. In other words, the hourly output from intermittent renewables is distributed across all generation units in proportion to their nameplate capacity.

3. Nuclear generation units are assigned a marginal cost. The maximum output of nuclear power plants is given by actual hourly plant-level generation data. We adjust the maximum and minimum capacity of nuclear power plants to a narrow band ($90-110\%$) around the actual generation to model the flexibility of nuclear power plants.

4. Reservoir hydropower generation units are assigned a marginal cost. The daily output from reservoir hydropower plants in country j must equal the actual daily generation from reservoir hydropower in that country, but the maximum hourly output from reservoir hydropower generation units is the nameplate capacity.

5. We impose a ramping restriction on fossil-fired generation units (hard coal, lignite and natural gas), which restricts the change in the output across hours. This ramping restriction depends on the particular fuel used in the generation unit (10 %, 10 % and 20 % for lignite, hard coal and natural gas respectively).

We have described the data we use to construct the economics dispatch problem, marginal costs and capacity constraints in detail in in the previous section. We solve the following linear optimization problem:

$$\min_{Q_{t,1},Q_{t,2},\ldots,Q_{t,20416}} \sum_{i=1}^{20416} p_{t,i}Q_{t,i} \tag{1}$$

s.t.

$$\sum_{i=1}^{20416} Q_{t,i} = \sum_{k=1}^{5324} D_{t,k} \tag{2}$$

$$LB_l \leq \sum_{k}^{5324} PTDF_{lk}(\sum_{i}^{20416} Q_{t,i} \times \mathbb{1}_{ik} - D_{t,k}) \leq UB_l \tag{3}$$

$$Q_{t,i} \in (Q_{t,i}^{min}, Q_{t,i}^{max}) \tag{4}$$

for $\forall i \in (1, ..., 20416)$, for $\forall l \in (1, ..., 6980)$ and for $t \in (1, ..., 24)$

$$|Q_{t,i} - Q_{t+1,i}| < Ramprate_i \tag{5}$$

for $\forall i \in FP$ (where FP is the set of all fossil-fired generation units) for $t \in (1, ..., 23)$ and

$$\sum_{t=1}^{24} \sum_{i=1}^{HU_C} Q_{t,i} = \sum_{t=1}^{24} HydroGeneration_{C,t} \tag{6}$$

for $\forall C$, where HU_C is the set of reservoir hydropower generation units in country C and $HydroGeneration_{C,t}$ is the output from all reservoir hydropower generation units in country C at hour t.

We solve this optimization problem for 20416 generation units across 5324 nodes connected to a power grid consisting of 6980 transmission elements with lower and upper bounds LB_l and UB_l for real power flows (recall that line flows are directional, which implies that $LB_l = -UB_l$). Line losses are not considered in our model. We restrict the number of nonzero shift factors one node can have, which implies that very small shift factors are rounded to zero.

Including minimum safe operating limits ($Q_{t,i}^{min}$ turns this problem from a simple linear optimization problem to a mixed-integer programming problem, which significantly increases the computational burden of solving the model. In practice, we observe that the minimum safe operating limit constraint is very rarely binding and has very small effects on the simulated outcomes. We thus use an alternative method to include minimum safe operating limits to our problem by solving the linear optimization model in two stages. In the first stage (day-ahead market clearing), we solve the optimization model using forecast load and intermittent renewables (solar and wind) generation data, ignoring minumum safe operating limits. We then observe the day-ahead dispatch and re-optimize the model using realized demand and intermittent renewables generation data (real-time operation). In the second stage, only fossil-fired units that were dispatched in the day-ahead market clearing (i.e., they had nonzero output) can be used, and their output is subject to minimum and maximum safe operating limit constraints. This adds an additional layer of plausibility to our comparison between simulated and observed dispatches, as the observed data from 2023 was subject to a similar two-stage process. The key difference, however, is that in the observed (zonal) market clearing, the second stage also includes redispatch to solve physical infeasibility (in addition to redispatching in response to demand and intermittent renewable output realizations).

In our model, the day-ahead dispatch is already physically feasible, and redispatch is only needed to respond to demand and intermittent renewables generation realizations. Thus, our optimization model is subject to the same uncertainty as the real-world market-clearing process we are comparing our results to. We do not consider any foresight or strategic dispatch that the market operator could use to optimally prepare for the demand and intermittent renewables generation realizations, and it is unclear whether operators of currently implemented nodal markets strategically dispatch additional generation (or use other strategies) to anticipate these realizations.

The nodal price at node k at time t is defined as the value of the partial derivative of the optimized value function with respect to $D_{t,k}$:

$$P_{t,k} = \frac{\partial}{\partial D_{t,k}} \mathcal{L} = \underbrace{\lambda_t}_{Energy\ component} + \underbrace{\sum_{l}^{L} PTDF_{lk}(\tau_{t,l}^{LB} - \tau_{t,l}^{UB})}_{Congestion\ component} \tag{7}$$

Where the energy component is the shadow price associated with the power balance constraint[11] and the congestion component is the sum of the differences in the two shadow prices associated with the transmission constraints between nodes, weighted using the PTDF/shift factor matrix. While this expression may be helpful in understanding how nodal pricing incorporates the different constraints involved in the generation and transmission of electricity into the final price faced by consumers and producers, it is important to note that the two components are always defined in reference to a specific a reference bus, and in a large system of nodes only make sense as bookkeeping values. It may be tempting to interpret the congestion element of the nodal price as a kind of externality that consumption in a particular node causes on top of the power balance element, but this interpretation would be inaccurate. An increase in line loadings caused by load in a specific node can be considered an externality, but this externality has a well-defined monetary cost only when a line reaches its thermal capacity. The nodal price measures the cost to service load at a specific node, and measures the change in the overall cost to serve demand in the entire system caused by an increase in demand in that node. This cost may reflect the necessity of both increasing and decreasing generation in other nodes needed to satisfy all transmission constraints.

While we do not attempt or claim to accurately predict prices or dispatch quantities in a hypothetical European nodal wholesale market, our linear optimization problem is essentially the same (albeit slightly simplified) that is solved by market operators in real-world

[11] The energy component is equal to the marginal cost of the marginal unit of the entire system

wholesale markets that employ nodal pricing. Real-world nodal wholesale markets may allow a variety of complex bids in addition to simple price-quantity bids; we assume that ramping restrictions limit the output from fossil-fired generation units, but our "market clearing" is entirely based on simple price-quantity bids. We use the following static marginal costs for renewable (and other "must-run") technologies:

Generation technology	marginal cost (€/MWh)
Solar	-20
Wind	-5
Hydro (run-of-river)	0
Hydro (pumped storage)	0
Nuclear	5

Our static marginal cost assumptions for these technologies are in line with the assumptions used in the ENTSO-E analysis on locational marginal pricing (*Report on the Locational Marginal Pricing Study of the Bidding Zone Review Process* (2022)). For reservoir hydropower generation units, we use the actual average monthly zonal prices as marginal cost estimates to model the fact that the relevant marginal cost for reservoir hydropower units is the opportunity cost of producing, i.e., forgoing production in the future. We acknowledge that this method is far from perfect, but considering that reservoir hydropower represents a reasonably small share of all electricity generated in Europe, this assumption is likely to not have major implications for our results. We furthermore note that we do not expect our average country-level simulated prices to differ from actual observed prices by a large amount. In any case, the implication from this assumption is that the accuracy of our results on nodal prices in countries where reservoir hydropower represents a large share of all electricity generation (Norway and to a lesser extent Sweden) may suffer. We describe the method we use to obtain marginal cost estimates for fossil-fired generation units in section 4.2.

3.4 The power grid

We use the publicly available ENTSO-E grid map to model the European power grid. This data has been complied from the grid map to a more easily usable form by Hoersch et al. (2018). This data includes information about all buses, lines (AC and DC) and transformers. The data on lines only includes information about voltages and the number of circuits. We apply standard assumptions to obtain line reactances and thermal capacities. We perform sensitivity analysis on the effect of line reactances and thermal capacities on nodal prices.

More accurate data on these line parameters would yield a more accurate nodal price simulation, but such data is currently unavailable in the scale we require for the scope for our analysis.

To obtain line shift factors, we apply standard DC power flow assumptions (as detailed, for example, in Seifi & Sepasian (2011)):

- Line resistances are ignored
- Tap settings are ignored
- Voltage angle differences are assumed to be small
- Bus voltage magnitudes are set to 1
- All transmission lines are assumed to have the same impedance characteristics that only depend on voltage and the length of the line

Our analysis is thus based on the DC power flow approximation, which ignores reactive power flows. We can then form the PTDF/shift factor matrix by only using information about the layout of the power grid and the reactances of power lines (Ronellenfitsch et al. 2014). The DC power flow approximation is widely used in power system simulations since shift factors in the DC approximation do not depend on existing line flows; this is a key assumption we use to format the economic dispatch problem as a linear optimization problem. Using an AC power flow model would improve the accuracy of power flows, but AC power flow models are nonliear, which would make solving the model infeasible. We reiterate that DC power flow assumptions are used by existing operators of nodal markets to calculate shift factors. We give more details on the construction of the PTDF matrix in section 4.1.

The resulting PTDF matrix is an estimate of actual grid conditions for two reasons. First, we do not have access to accurate information about the impedance characteristics of individual transmission elements (lines and transformers). Second, the DC power flow assumptions ignore several aspects of the physics of electricity and the power grid. One of the key simplifications is the (implied) ignoring of line losses. This results in a PTDF matrix which unrealistically implies that increasing load in node i will affect all transmission elements in the grid, however small those effects might be. This is why ISOs that use nodal pricing apply a threshold to round very small elements in the PTDF matrix to zero. Both the California ISO and ERCOT use a threshold of 2 %. Using the same threshold on our PTDF matrix yielded on average 1340 nonzero entries for each node in the network. This brings the share of zero entries in the PTDF matrix to 80%.

4 Data

We solve an optimization model where the objective is to minimize the cost of meeting a set of nodal demands while respecting the aggregate power balance constraint (supply must equal demand), a set of transmission constraints for transmission elements, and a set of generation capacity constraints for all generation units. The solution to the problem is a set of dispatch quantities. Nodal prices are then calculated using dual variables of the constraints by summing a shift-factor weighted sum of transmission capacity dual variables corresponding to node n and the dual variable of the power balance constraint. The data we use to estimate the model is outlined in the table below.

Data	Source
Transmission system data	PYPSA-Eur (from ENTSO-E grid map)
Generation unit technical data	PYPSA-Eur and Global Energy Monitor
Hourly demand in nodes	ENTSO-E and European Energy Atlas
Day-ahead load forecast	ENTSO-E
Hourly country-level supply of intermittent renewables	ENTSO-E
Day-ahead country-level intermittent renewables supply forecast	ENTSO-E
Unit-level hourly output of large units	ENTSO-E

Table: Outline of data used in the model

4.1 Transmission system

We obtain data on the European electricity transmission system from the PYPSA-Eur energy system optimization model (Hoersch et al. 2018). This data has been compiled from the European power grid map published by ENTSO-E. We include all transmission elements and buses in the dataset that are located within the countries we select to be a part of the simulation (figure 11). The transmission elements in the dataset consist of DC power lines, AC power lines of different voltages (132 Kv, 220 Kv, 300 Kv, 380 Kv, 500 Kv and 700 Kv), as well as transformers (between different voltage levels) and converters.

The other part of the transmission system data is data on the buses, or nodes of the network. We use the terms "node" and "bus" interchangeably. Transmission elements are modelled as unidirectional, which means that all elements have a "sending" and "receiving" bus. The directionality of transmission elements is arbitrary, and has no particular implications for the model, as long as the direction of transmission elements stays constant. The data on buses includes information about the voltage of the bus and exact location. The length of transmission elements (when applicable) is included in the transmission element data from PYPSA-Eur. The database includes detailed information of the exact shape of transmission lines, which is used to calculate the length of transmission lines. Converters

and transformers are modelled as transmission elements of length 0. They are connections between two buses of different voltages in the same location.

Our data includes the voltage, type, and length (when applicable) of the transmission elements, which we use to estimate the maximum thermal capacity and impedance using assumptions from engineering literature. The maximum thermal capacity and impedance of transmission elements are the two key factors we use to construct thermal capacity constraints, which bound the set of allowable nodal net balances. A detailed explanation of how we construct these constraints follows in the rest of this subsection. We outline the technical assumptions used to estimate the impedances of transmission elements in appendix 3.

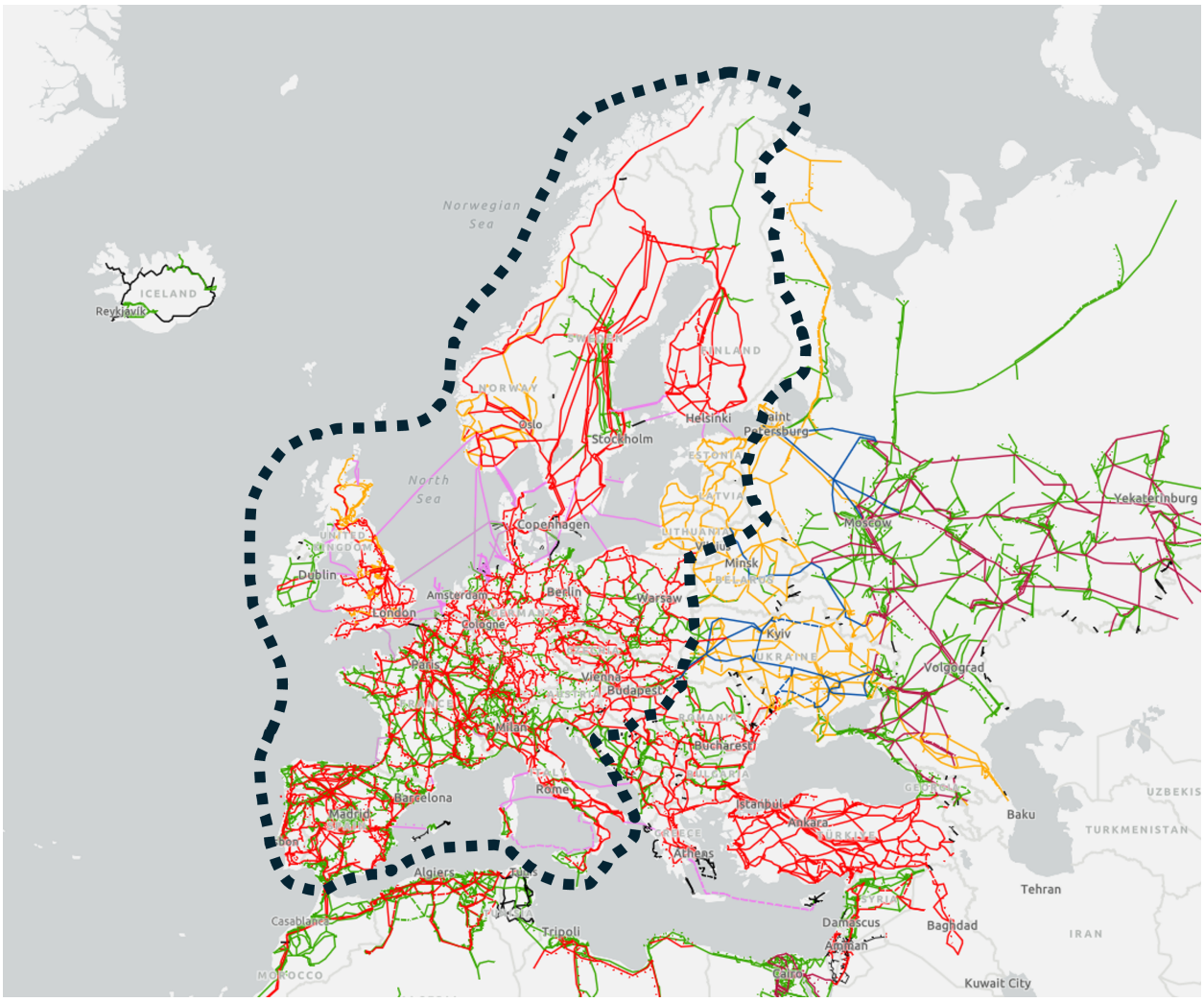


Figure 11: The Entso-E grid map was used to construct the network model used in our optimization model. Outlined are the countries included in our model (*ENTSO-E Grid Map* (2025)).

In power systems analysis, nodes are sometimes classified into demand and supply nodes. In the engineering literature, a bus is usually defined as an electrically distinct point in a power system, which is to say it is a point in the transmission network where multiple transmission elements intersect, or generators, large loads or distribution networks are connected to the system. The same definition is used in the economic applications of power systems analysis. In some applications, nodes can thus be classified into demand and supply nodes. As per the previous definition, a demand node is a node where a distribution network is connected to the power grid, and a supply node is likewise a node where a generator/generators

are connected to the grid. While we do use this distinction in our analysis, we do not restrict the model by defining a set of supply and demand nodes before the simulation and using this classification to match generation units and loads to nodes. We match load and generators to all nodes (based on distance) using only the following restriction: in locations where two or more nodes are connected to each other with transformers, we only match load and generation units to the node with the larger voltage. After we carry out the simulation, we observe the average demand and output and use this information to classify nodes into demand nodes, renewable supply nodes and thermal supply nodes, depending on the average balance of demand and thermal and renewable energy generation. In our model, nodes can thus have both generation units and a load. While this may not reflect the underlying reality perfectly, we believe that this is still the superior way to approach modelling the European power system using the data that we have. Crucially, we do not have information on which nodes of the transmission system connect to distribution grids. We prefer to keep the treatment of nodes a simple as possible, and use the heuristic that the nearest node in terms of distance the likeliest to serve load in some location, or connect a generation unit to the transmission system. We classify nodes into demand nodes and supply nodes of different types based on average simulated generation and demand and use this classification in the analysis of our results.

We make only very minor modifications to the transmission system data from Pypsa-Eur. In cases where two nodes of different voltages are located in exactly the same location and are not connected by a transformer, we add a transformer between the nodes. The Pypsa-Eur transmission system data has been compiled from the ENTSO-E grid map, again with slight modifications. In particular, the authors of Pypsa-Eur add nodes in locations where multiple transmission lines intersect, but no node exists in the ENTSO-E grid map (Hoersch et al. (2018)).

The transmission constraints are of the form $LB_l \leq \sum_k^Z PTDF_{lk}(\sum_i^N Q_i \times \mathbb{1}_{ik} - D_k) \leq UB_l$, where LB_l and UB_l correspond to the thermal limits of transmission element l[12], $Q_i \times \mathbb{1}_{ik}$ is the generation of all generation units in node k, D_k is demand in node k, and $PTDF_{lk}$ is the power transfer distribution factor corresponding to node k and transmission element l. The term $(\sum_i^N Q_i \times \mathbb{1}_{ik} - D_k)$ is thus the power balance at node k, i.e., the difference between nodal generation and load. $PTDF_{lk}$ is the effect of a one-unit increase of demand in node k on the flow on transmission element l. It follows that the transmission constraint l is the effect of all power balances in the system on the flow on transmission element l. Transmission elements are directional, i.e., negative flows imply a different direction

[12]As transmission lines are directional, $LB_l = -UB_l$, which is to say that negative flows are flows from the receiving bus to the sending bus, but they are represented by a negative flow from the sending bus to the receiving bus. The flow on a line can be zero, so no lower bound on the magnitude of flows exist.

compared to positive flows. It follows that $LB_l = -UB_l$.

We use data from the European transmission system to construct the transmission constraints. In order to do this, we need three things: the thermal constraints of transmission elements (or line flow constraints) (LB_l and UB_l), the demand and supply at each node, and the PTDF matrix. To obtain line flow constraints, we use the PYPSA-Eur data on all transmission elements and use the details included in the data to apply standard assumptions form the engineering literature. To obtain the PTDF matrix, we use data on transmission elements and buses from PYPSA-Eur and apply standard DC power flow assumptions.

To obtain nodal supply, we use data from the PYPSA-Eur power plant database and the Global Energy Monitor. The PYPSA-Eur database is an open-source database of all generation units in Europe, complied from multiple sources. The authors compare this database to proprietary power plant databases, and find to be accurate. This database contains information on the exact location and country of each generation unit, its main "fuel" (solar, wind, natural gas, lignite, hard coal, etc.), specific technology (run-of-river or water reservoir for hydro, CCGT or steam turbine for natural gas, etc.), commissioning year and nameplate capacity. The dataset also contains other technical that we do not use. We perform statistical estimation using the retrofit year variable in the dataset, more details on this later in this section. We use the exact location of the generation unit to match generation units to nearest nodes based on distance. In the case that there are multiple nodes in the same exact location, we match generation units to the node with the highest voltage. We use information about the exact fuel type and technology used by the generation unit to determine marginal costs. We use the commissioning year variable to adjust the heat rate for thermal generation units when estimating marginal costs. We furthermore use the Global Energy Monitor (GEM) Goal and Natural Gas generation unit to obtain more detailed information about the exact technology and fuel type used by a power plant. The GEM databases include more fuel types (different types of hard coal and more exact natural gas turbine technologies). We match these databases using location and generation unit name.

To obtain nodal loads, we use hourly demand data from ENTSO-E and the European Energy Atlas. The European Energy Atlas is a 1 km $\times$ 1 km resolution map of the European Union, where each 1 km $\times$ 1 km box includes the yearly consumption of electricity at this location. We then match each box to the nearest node within the same country (this is equivalent of forming Voronoi cells around nodes), again with the restriction that if there are two or more nodes at the same location, only the node with the largest voltage will be assigned demand. We then calculate the share of total demand of a country for all nodes by dividing the total yearly electricity consumption at each node with the total yearly consumption of the corresponding country. We obtain hourly time seria of total load in the countries we include in our simulation from ENTSO-E, and distribute this hourly demand

across all nodes using the total demand share we obtained using the Energy Atlas. For countries that are not included in the Energy Atlas but are included in our simulation (The United Kingdom and Switzerland), we obtain a proxy of the share total demand at each node using a population distribution map and an analogous process of Voronoi cells. While we acknowledge that the demand shares we obtain using the distribution of population are somewhat inaccurate, we include these non-EU countries in our simulation due to their high level of interconnectedness to the European power grid. The Pypsa-Eur optimization model estimates nodal demands using the geographical distribution of population and GDP. Our estimates of nodal demands are likely more accurate than those used in Pypsa-Eur, and comparable in accuracy for the United Kingdom and Switzerland.

We then describe how how we construct the power transfer distribution (PTDF) matrix using data of the power grid and by applying parameter and DC power flow assumptions. The PTDF matrix has 5324 rows (the number of buses in the power system) and 6980 columns (number of transmission elements). The element (l, n) of the PTDF matrix (often called the shift factor of node n for line l; hence the PTDF matrix is also called the shift factor matrix) corresponds to the effect of a one-unit increase in load in node n on the flow on transmission element l. All transmission elements, including transformers, are assigned shift factors. The matrix describes the operation of the power grid under DC load flow assumptions. As the name suggests, these assumptions mean that the transmission network is modelled as one that consists only of DC power lines. The key implication of these assumptions is that the operation of a DC network does not depend on existing line flows. While the AC power flow problem (solving line flows in an AC network based on nodal power balances) is nonlinear, the DC power flow problem is linear. We construct the PTDF matrix by assigning all transmission elements a single value for impedance. Electrical impedance is defined as the combined effect of resistance and reactance of a transmission element. With DC power flow assumptions, we ignore resistances and only include reactances. Electrical impedance can be explained heuristically as the "difficulty" that electricity faces while travelling through a transmission element. Since (again heuristically) electricity travels through "the path of least resistance", we essentially collapse all information about the aspects of this "difficulty" into the impedance characteristic, and use the information to determine the path that electricity takes when being transmitted from node a to b. In complex networks, this path consists of multiple branches, with smaller flows through paths with more "difficulty". To our knowledge, all system operators that use a nodal-pricing wholesale market use similar DC power flow assumptions to construct the PTDF matrix.

The formula for the PTDF matrix is

$$PTDF = B_d I^t (I B_d I^t)^{-1} S \tag{8}$$

Where B_d is an 6980×6980 diagonal matrix of transmission element susceptances. We list all transmission elements in the power system in an arbitrary order, assign them indices and calculate their electrical impedances based on standard assumptions from engineering literature. In the case of transmission lines, this value depends on voltage and transmission line length. For transformers, this value depends on the voltages at each end of the transformer. We then form the diagonal matrix by placing the impedance of the i:th element of the list of transmission elements in the (i, i) entry of the matrix and set all off-diagonal values to zero.

I is the 5324×6980 node-transmission element incidence matrix. For each transmission element of the system (rows), the incidence matrix tells which buses are the receiving and sending buses (columns) of the corresponding transmission element. Row l consists of $5324-2 = 5322$ zero elements, and one 1 and one -1 corresponding to the sending and receiving bus in the network. We construct the incidence matrix by again listing all nodes in the network and giving them indices. With this, row l of the incidence matrix is constructed in the following way: let i denote the index of the sending bus associated with transmission element l and j denote the index of the receiving bus (recall that in the model, transmission lines and other elements are directional). We set the i:th element of row l of the incidence matrix to 1, we set the j:th element of row l of the incidence matrix to -1, and we set all other elements to be 0. We repeat this step for all rows corresponding to all transmission elements of the transmission system to construct the incidence matrix. An example of an incidence matrix is illustrated below:

$$\overbrace{\phantom{\begin{matrix}0&1&0&-1&\cdot&\cdot&\cdot\end{matrix}}}^{\text{5324 columns}}$$
$$\left.\begin{matrix}\\\\\\\\\\\\\\\\\end{matrix}\right\}\text{6980 rows}$$
$$\begin{pmatrix} 0 & 1 & 0 & -1 & \cdot & \cdot & \cdot \\ 1 & 0 & -1 & 0 & \cdot & \cdot & \cdot \\ \cdot & & & & & & \\ \cdot & & & & & & \\ \cdot & & & & & & \\ -1 & 0 & \cdot & \cdot & \cdot & 0 & 1 \end{pmatrix}$$

Finally, S is the slack distribution matrix. The slack distribution matrix is a 5324×5323 matrix that determines the reallocation policy between nodes. Essentially, the reallocation policy gives the change in output in node k as a response to a one-unit increase in load in node n. We set the reallocation value of all nodes for all nodes to be equal to the share of total generating capacity in a particular node. The choice of slack is more or less arbitrary since the choice of slack affects the way the nodal prices are calculated based on shadow prices.

4.2 Generation units

To obtain data on the capacities and marginal costs of power plants in Europe, we use the PyPSA-Eur power plant database, as well as the Global Energy monitor database on coal and natural gas production units. This data contains information about the nameplate capacities, exact locations, production technologies, fuel types and ages of production units on the generator level. The PyPSA-Eur power plant database is considered to be the most accurate publicly available database of European power generation units. We augment this data with the Global energy monitor data on fossil-fired generation to obtain more detailed data on the generator technologies and types of fuels used by units.

To estimate the marginal costs of fossil-fired generation units, we use the methodology proposed by Biggar & Hesamzadeh (2014), and used previously in (for example) Schram et al. (2019) and Alikhani et al. (2023):

$$MC_n = \frac{fp_n}{\eta_n} + \frac{ef_n}{\eta_n} \times ep + voc_n \tag{9}$$

Where

- n = index of generation unit
- fp_n = price of fuel used by generation unit n (in $\frac{€}{MWh}$)
- ef_n = emission factor of the fuel used by unit n (in $\frac{tCO_2}{MWh}$)
- ep = emission price (in $\frac{€}{tCO_2}$)
- η = degree of efficiency (conversion efficiency, given as a percentage by dividing the equivalent Btu content of a kWh of electricity (3,412 Btu) by the heat rate (also given in Btus))
- voc_n = variable operational and maintenance costs

We use unit-level data on heat rates, given by the generator technology and the age of the generation unit based on standard assumptions. Our data for the heat rates of coal-fired power plants is from the Global Energy Monitor power plant database, and our data for the heat rates of gas-fired power plants is from the US Department of Energy Electric power annual (*Electric Power Annual 2023* 2023). The heat rates are expressed in Btu/KWh. The marginal fuel cost is calculated by multiplying the fuel cost (expressed in terms of €/MWh)

with $\frac{1}{\eta_n}$, where $\eta_n = \frac{KWh}{Btu} \times HR\frac{Btu}{KWh}$, i.e., the thermal efficiency of generation unit n. Efficiency is unitless.

To obtain fuel costs for fossil-fuel fired generators, we use the spot price of natural gas in the Dutch TTF and the API2 CIF hard coal Northwestern Europe benchmark price. Our data on natural gas and lignite fuel costs is in $\frac{€}{MWh}$, and our data on hard coal fuel costs is in $\frac{€}{tCoal}$. We use standard assumptions on the energy content of hard coal. We ignore variable operation and maintenance costs.

Our data for the fuel costs of hard coal is expressed in euros per tonne. We assume that the energy content of one tonne of hard coal is 24 MMBtu, or 7.03 MWh, which allows us to express the price of hard coal in terms of tonnes/MWh. Our data for the fuel costs of lignite is expressed in euros per gigajoule. One joule is equivalent to one watt-second ($J = W \times s$), which implies that one gigajoule is equivalent to 3.6 megawatts. This allows us to express the fuel cost of lignite in euros per megawatt hour. Our data for the fuel cost of natural gas is expressed in euros per megawatt hour, which means that no unit conversions are necessary.

The marginal emission or carbon cost is calculated by multiplying the marginal emission rate with the emission cost, which is expressed in euros per tonne of carbon dioxide. The marginal emission rate is calculated by multiplying the emission factor of the relevant fuel with $\frac{1}{\eta_n}$. η_n is unitless, which implies that the marginal emission rate has to be expressed in tonnes of carbon dioxide per megawatt hour. The emission factor is a measurement of the carbon dioxide contained in one unit of a particular fuel. Our data on the emission factors of fuels is expressed in tonnes of carbon dioxide per terajoule, which we need to convert to tonnes of carbon dioxide per megawatt hour, to obtain a marginal emission cost in euros per megawatt hour. Again using the fact that one joule is equivalent to one watt-second ($J = W \times s$), one terajoule is equivalent to 3600 megawatt hours, which we use to convert the emission factors to the correct units.

Fuel type	Emission factor (TnCO2/TJ)	Source
Coal (subbituminous)	101	2006 IPCC guidelines
Coal (bituminous)	96.1	2006 IPCC guidelines
Coal (anthracite)	94.6	2006 IPCC guidelines
Lignite (Poland)	111.2	Eurostat
Lignite (Germany)	110.8	Eurostat
Lignite (Hungary)	105.6	Eurostat
Lignite (Slovenia)	102.1	Eurostat
Lignite (Czech Republic)	94.6	Eurostat
Natural Gas	50	US DOE

Table: Emission factors used in marginal cost estimation with sources. We use IPCC data on the emission factors of different types of coal (*IPCC Guidelines for National Greenhouse Gas Inventories* (2006)), Eurostat data for the marginal emission factors for lignite (*Production of lignite in the EU - statistics* (2025)), US EIA data on the emission factor of natural gas (*US Energy Information Administration: Carbon Dioxide Emissions Coefficients* (2025))

Generator technology	Heat rate (Btu/KWh)	Source
Coal, subcritical	8 702	Sargent & Lundy, 2009
Coal, supercritical	8 409	Sargent & Lundy, 2009
Coal, ultra-supercritical	8 272	Sargent & Lundy, 2009
Coal, CFB	8 702	Sargent & Lundy, 2009
Coal, IGCC	7 528	Sargent & Lundy, 2009
Natural gas, steam generator	10 314	US DOE
Natural gas, gas turbine	11 010	US DOE
Natural gas, internal combustion	8 900	US DOE
Natural gas, combined cycle	7 549	US DOE

Table: Heat rates used in marginal cost estimation with sources. We use EIA data on the heat rates of different natural gas technologies (*Electric Power Annual 2023* (2023); table 8.2) and data from a study by Sargent & Lundy LLC for the US EIA (*New Coal-Fired Power Plant Performance and Cost Estimates* (2009)) for the heat rates of different coal combustion technologies.

We present all assumptions we make about the emission factors of different types of fuels and the heat rates of different types of generation units (above). We calculate average marginal fuel and emission costs based on average input costs for the year 2023. The average cost of natural gas was 40.6 €/MWh, the average emission allowance cost was 82.3 €/tCO2,

and the average cost of hard coal was 115.3 €/tonne, which is equivalent to 16.4 €/MWh. We assume a constant lignite fuel cost of 2.5 €/GJ, which is equivalent to 9 €/MWh. Our heat rate assumptions suggest that the average efficiency of lignite and hard coal units is 37 %. The efficiencies for natural gas plants are 45 % for combined cycle units, 38 % for internal combustion units and 31-33 % for steam generator and gas turbine units.

	Costs expressed in (€/MWh)		
Fuel type	marginal fuel cost	marginal emisssion cost	Total
Hard coal	42.6 − 44.6	73.7 − 80.1	116.3 − 124.7
Lignite	23.4 − 24.5	77.8 − 90.2	101.2 − 114.7
Natural gas, steam generator	122.7	50.6	173.3
Natural gas, gas turbine	131.0	54.1	185.1
Natural gas, internal combustion	105.9	43.7	149.6
Natural gas, combined cycle	89.8	37.1	126.9
	Costs expressed in (€/MMBtu)		
Fuel type	marginal fuel cost	marginal emisssion cost	Total
Hard coal			34.1 − 36.6
Lignite			29.7 − 33.6
Natural gas, steam generator			50.8
Natural gas, gas turbine			54.3
Natural gas, internal combustion			43.9
Natural gas, combined cycle			37.2

Table: average marginal fuel, emission and total costs for different fuels and generation technologies given average input prices and assumptions on heat rates and emission factors

These estimates can seem unusually high, but a part of why it may be difficult to assess the plausibility of our results is different conventions and units used in pricing. In particular, it is often the convention in North America to express prices in terms of MMBtus instead of MWh. We contrast our estimates to comparable marginal cost estimates with input price data from California. The average California natural gas citygate price was 7.21 $/Mcf (dollars per thousand cubic feet) (*Natural Gas Citygate Price in California* (2025)). The average heat content of natural gas in the United States was 1.038 MMBtu/Mcf (*Conversion Rates for Natural Gas* (2025)) Using the fact that one megawatt hour is equivalent to 3.412 MMbtu, the average California citygate price was approximately 24 $/MWh in the year 2023. The price difference between Henry Hub (which the citygate price follows closely) and the Dutch TTF natural gas has historically been quite small, but increased notably due the disruption of natural gas supply to Europe as a result of the restriction of Russian gas supply in 2021 and the Russian invasion of Ukraine in 2022, and has remained elevated since.. The average auction price for the California carbon allowance price in the year 2023 was approx-

imately 32.2 $/TnCO2. Using our heat rate and emission factor assumptions for combined cycle plants, we find that the marginal fuel cost of a combined cycle unit in California is 53.1 $/MWh and the marginal emission cost is 14.4 $/MWh, to a total of 67.4 $/MWh (57.5 /MWh and 15.6 /MWh, to a total of 73.0 /MWh using a 2023 average exchange rate of 1 USD = 0.92€). Using these values, the marginal fuel cost in Europe was approximately 56.1 % higher, the marginal emission cost was 137.8 % higher and the total marginal cost was 73.8 % higher in Europe compared to California.

Among our sample countries, lignite is used in electricity generation in Germany, Poland and the Czech Republic. We use data from Agora Energiewende (*Die deutsche Braunkohlenwirtschaft: Historische Entwicklungen, Ressourcen, Technik, wirtschaftliche Strukturen und Umweltauswirkungen* 2017) for lignite fuel costs in Germany. These estimates were used by Germeshausen & Wölfing (2020), and are consistent with the numbers used by industry experts (*Modern German lignite plant margins halve from 2024* 2024). Our main source for lignite fuel costs in Poland is Bloomberg (*Energy in Belchatow After Lignite: Future-proofing energy generation in Belchatow, Poland* 2022). Lignite fuel costs in the Czech Republic are not available, but previous studies suggest that the costs are almost identical to those in Poland (*Understanding Lignite Generation Costs in Europe* 2014). Potential inaccuracies in the fuel costs of lignite power plants are unlikely to have a large effect on our results, since lignite represents a fairly small part of all fossil fuel -fired generation. Lignite generation is also rarely the marginal generation technology (Germeshausen & Wölfing 2020), which implies that its influence on prices is not expected to be very large.

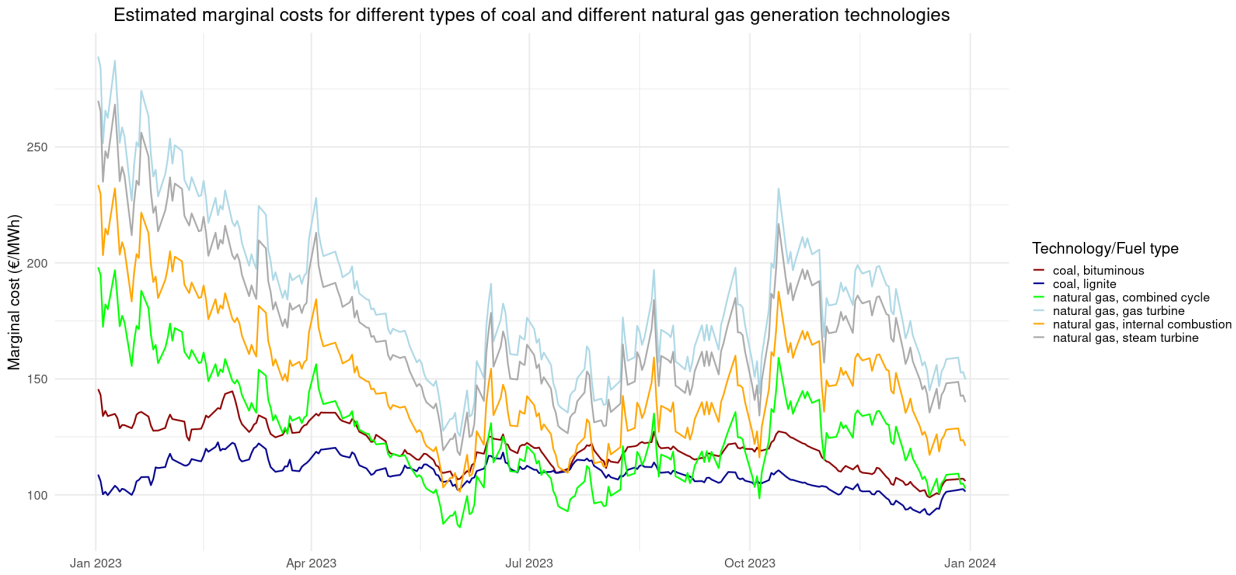


Figure 12: Estimated average marginal costs for different types of coal and different natural gas generation technologies (€/MWh) for the year 2023. The variation in lignite marginal generation costs is given by solely variation in the emission allowance price; the variation in hard coal and natural gas marginal generation costs is given by variation in the emission allowance price and fuel prices.

4.3 Choice of countries

The set of countries included in the simulation include most of continental Europe, the Nordic countries and Great Britain and Ireland. The choice of countries was made so that the simulation would cover most of continental Europe, specifically all countries in the CORE area. The Iberian peninsula, Italy, the Nordic countries and the British isles were included due to their integration to the CORE area, measured in the magnitude of cross-border flows. Romania was left out despite being a part of the CORE area, as it is likewise highly integrated to countries in Southeastern Europe, which were deemed to be not crucial to the simulation. There are also issues related to data reliability and availability for many of the Southeast European countries. The average magnitude of netted flows into and out of the simulation area per hour is 2805 MWh. This magnitude is very small compared to observed flows between countries inside the simulation area, implying that the treatment of imports and exports is unlikely to have a large effect on the simulation.

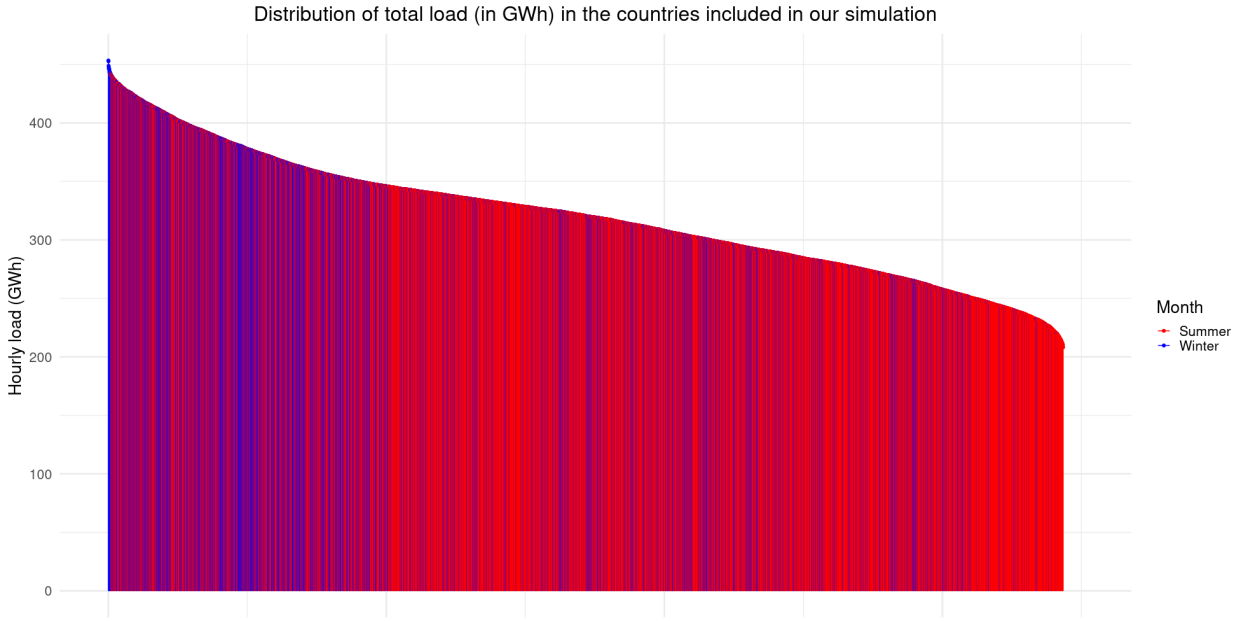


Figure 13: Distribution of total hourly observed loads in the countries included in our model. Winter months: October-March, Summer months: April-September

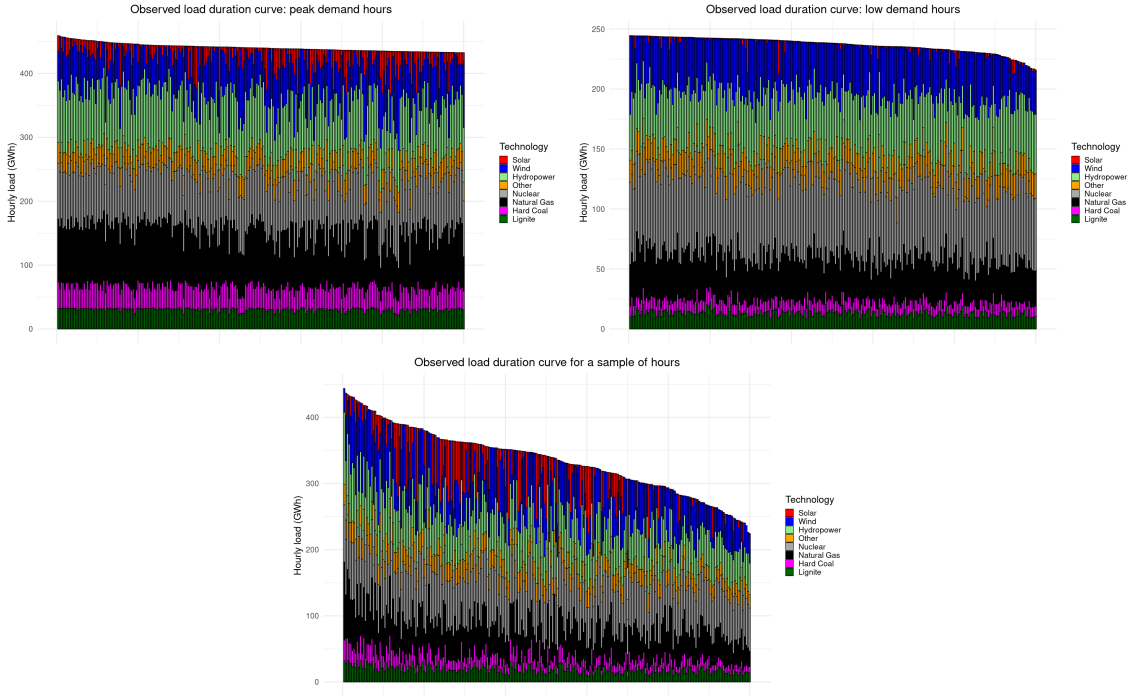


Figure 14: Observed load duration curves for i) peak demand hours, ii) low demand hours and iii) all hours (samples of 250 hours) (clockwise).

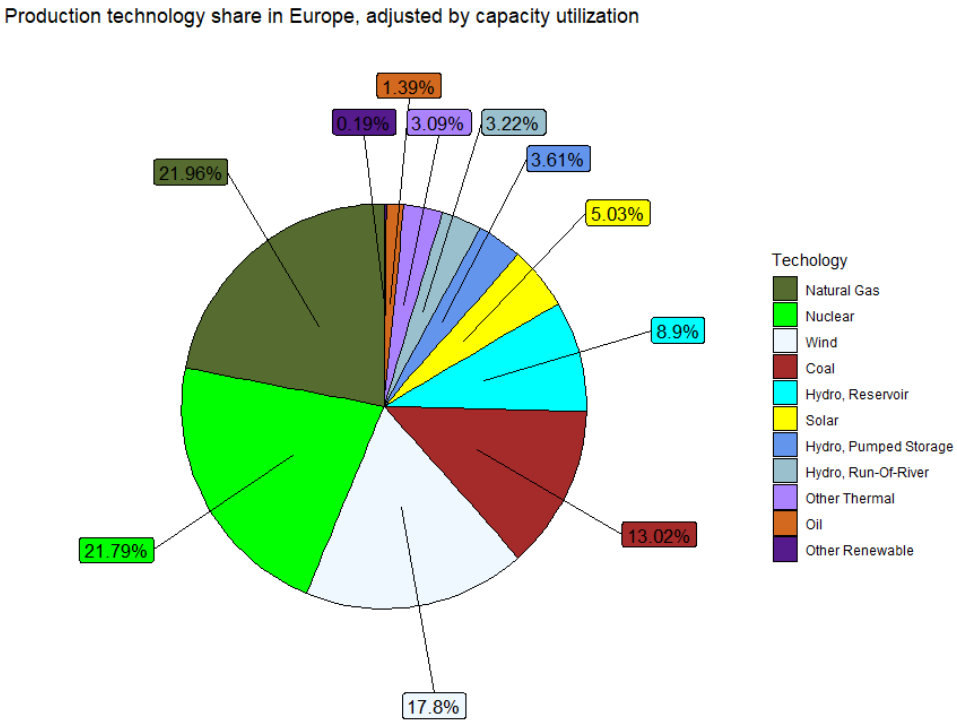


Figure 15: Share of all installed capacity in the countries included in our model, adjusted by country-level capacity utilization factors (IRENA)

5 Results

We solve the optimization model presented in section 4.3 for a sample of 50 days of the year 2023. We construct the objective function by calculating the daily marginal cost values using daily cost data on fuels and other inputs. We construct the transmission constraints by using the PTDF matrix, thermal capacities of transmission elements and hourly data on realized country-level demand and distributing it to the closest node (which we do not require to be in the same country) using data on the distribution of electricity consumption from the EU energy atlas. The PTDF matrix and the thermal limits of transmission elements do not vary across hours. We obtain capacity constraints for thermal generation units from the Pypsa-EUR power plant database. We obtain capacity constraints for solar, wind, hydropower and nuclear power plants using observed country-level output data from Entso-E, which we distribute across generation units based on their nameplate capacity. For solar and wind power, we set minimum and maximum generation to the (implied) observed output level. For hydropower and nuclear power plants, we set the minimum and maximum

generation to 95% and 105% of the observed output. For thermal generation units, we adjust the maximum capacity using the maximum country-level output observed in the data for 2023 for each fuel type (lignite, hard coal, natural gas). This ensures that we do not obtain simulated outputs for thermal generation units that are higher than the largest output observed in the data.

We present results on simulated quantities and prices and compare them to observed output and price data from the year 2023. We also present results on the capacity utilization of thermal generation resources, inframarginal rents (producer surpluses) as well as emissions.

5.1 Simulated and observed dispatch quantities

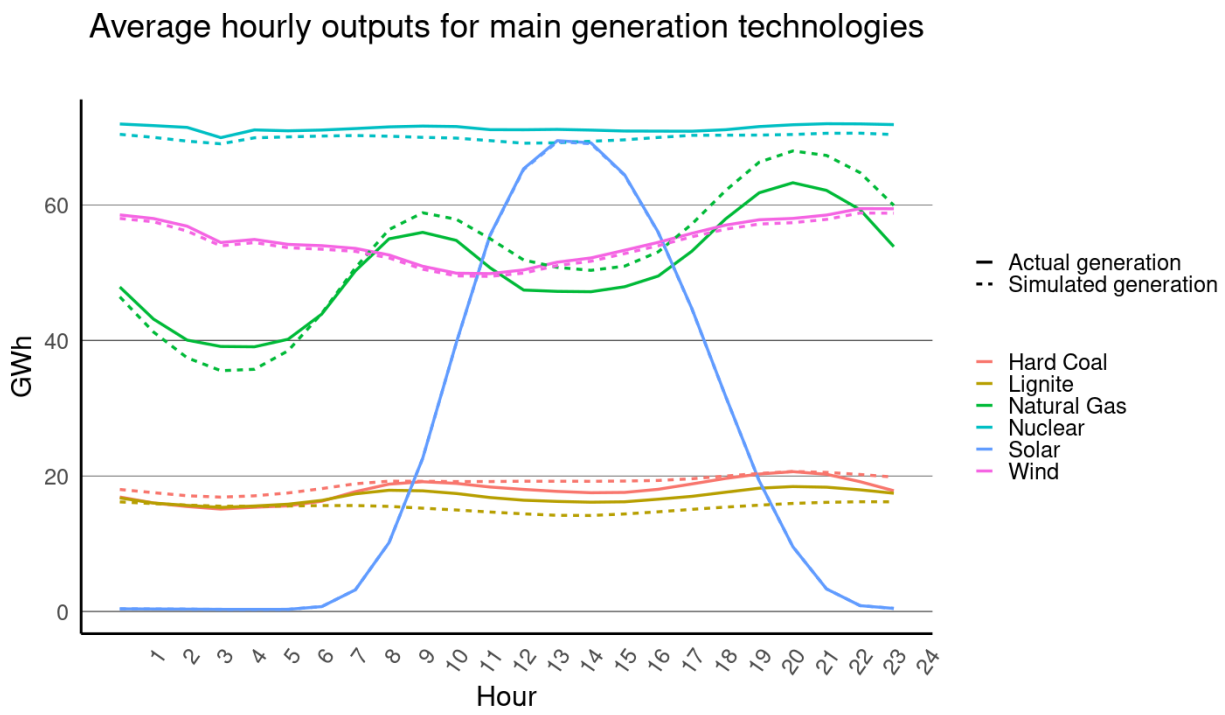


Figure 16: Results from our simulation: Average hourly simulated and actual dispatch for main generation sources (no. days = 50).

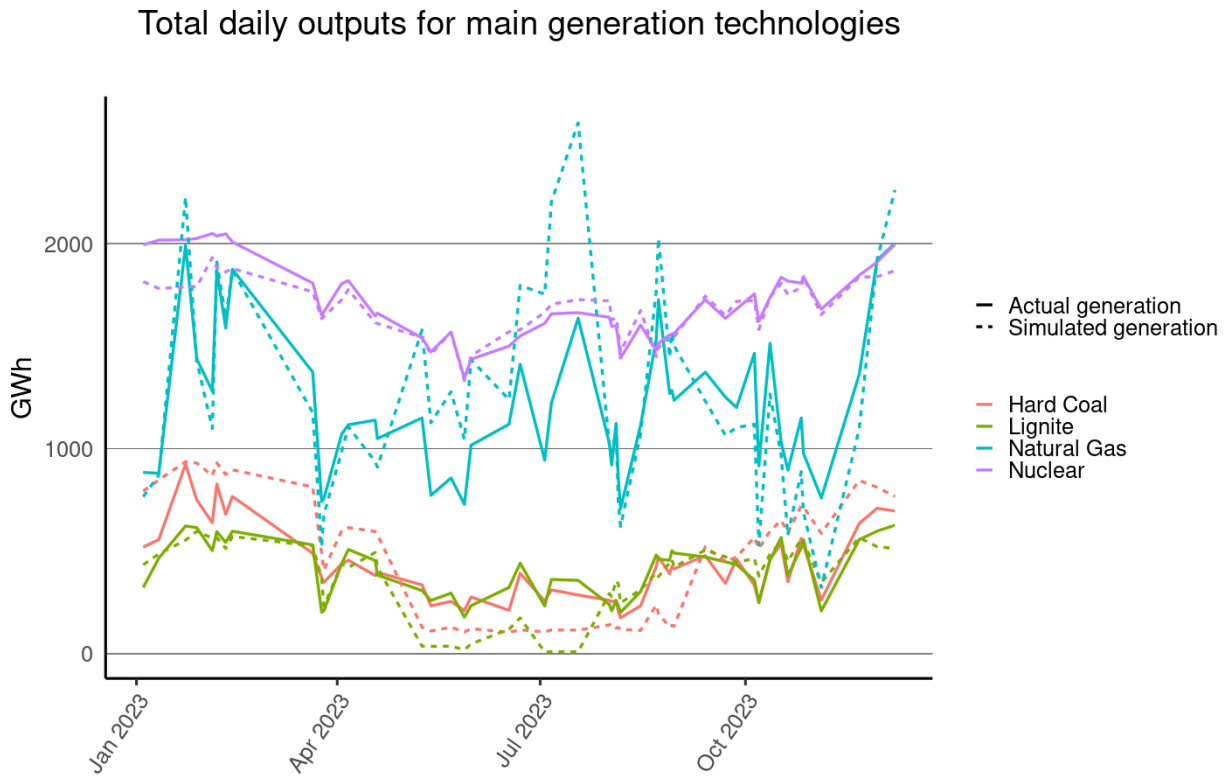


Figure 17: Results from our simulation: Total daily simulated and observed quantities for main generation sources (no. days = 50). Wind and solar outputs excluded for clarity.

We observe from figure 16 that on average, the results of our simulation are reasonably close to observed data. In practice, our simulated results are yielded by differences in marginal costs, that position lignite generation (and hard coal generation to a lesser extent) as baseline generation that runs regardless of variation in the output of intermittent renewables. This leaves natural gas generation as marginal generation that responds strongly to demand and renewable generation variation. We allow the output from these resources to be 5% above the observed for to reasons: to introduce some slack to the simulation (introducing too many static outputs may lead to primal infeasibility of the optimization problem), and to model the flexibility of these resources. Many nuclear generation units can be ramped up and down, so strictly enforcing the observed quantities is unrealistic (however, using the nameplate capacity of nuclear generation units may result in unrealistically high simulated outputs for some units). Our results however seem to show that there is only limited upward pressure in the output of nuclear generation units. On the aggregate level, it seems that more nuclear generation would have a very limited effect on achieving a cost-minimizing physically feasible dispatch. The results from hydropower suggest that there is consistent upward pres-

sure in the generation of hydropower, which is to say that the existing hydropower resources are important to achieving a cost-minimizing physically feasible dispatch. The generation of hydropower is subject to complex intertemporal optimization problems, which we do not currently model in our simulation. Introducing these intertemporal constraints to our simulation in some form would improve the accuracy of our model, and this is something we plan to do in the future. We note that figures 16 and 17 leave out smaller generation sources, which is why there is a slight difference in the total simulated and actual quantities.

We regress simulated natural gas output and the difference between simulated and observed natural gas output on total system demand, aggregate outputs from renewable generation sources that we take as exogenous, and fuel and emission allowance costs:

Table 1

	Dependent variable (aggregate natural gas unit generation):		
	Simulated output	Actual output	Actual - simulated output
	(1)	(2)	(3)
Hydro	-1.049^{***}	-0.519^{***}	0.530^{***}
	(0.117)	(0.028)	(0.111)
Nuclear	-1.184^{***}	-0.793^{***}	0.391^{**}
	(0.194)	(0.047)	(0.185)
Solar	-0.839^{***}	-0.681^{***}	0.158^{**}
	(0.068)	(0.016)	(0.065)
Wind	-0.912^{***}	-0.630^{***}	0.282^{***}
	(0.055)	(0.013)	(0.052)
Demand	0.972^{***}	0.608^{***}	-0.364^{***}
	(0.056)	(0.014)	(0.053)
P_{EUETS}	218.773^{**}	65.475^{***}	-153.299
	(97.844)	(23.688)	(93.085)
$P_{NaturalGas}$	$-2{,}706.545^{***}$	-506.584^{***}	$2{,}199.961^{***}$
	(199.755)	(48.362)	(190.041)
$P_{HardCoal}$	441.959^{***}	70.497^{***}	-371.462^{***}
	(104.372)	(25.269)	(99.296)
Observations (hours)	1200	1200	1200
R^2	0.903	0.991	0.501
Adjusted R^2	0.902	0.991	0.493
Residual Std. Error (df = 485)	19,548.790	4,732.875	18,598.140
F Statistic (df = 8; 485)	565.410^{***}	$7{,}049.105^{***}$	60.823^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

Table: Simulated and observed natural gas output and the difference between simulated and actual natural gas output regressed on renewable outputs, total system demand and average marginal costs of fossil-fired generation technologies. Similar regression tables for hard coal and lignite generation can be found in appendix 2.

We notice that the coefficients for simulated output for natural gas differ with the coefficients for actual output in magnitude, but the sign of the effect is always the same. The largest differences between the coefficients of the two models is for the input price variables, in particular for the price of natural gas and hard coal. We can therefore say that while out model predicts a supply response for natural gas to renewable generation that is mostly in line with the observed data from a zonal wholesale market, the predicted supply response to input prices is significantly higher than in the observed data from a zonal wholesale market. While we believe that this difference stems partly from the difference in pricing, it is obvious that our treatment of marginal costs as well as ramping restrictions, start-up costs and district heat generation (or the lack thereof) has an influence on this difference as well. The positive coefficient for emission allowance price (P_{EUETS}) on natural gas output is expected, as natural gas has a lower marginal emission rate compared to other types of thermal generation.

We also perform similar regression analysis for lignite and hard coal generation (see appendix 2). For these results, all coefficients for renewable output in both models are negative or statistically insignificant (nuclear for all simulated and actual lignite generation and actual hard coal generation). In these models, the coefficients for renewable generation are however larger in magnitude for actual output compared to simulated output. The coefficients for input prices are mostly as expected (natural gas price has a positive coefficient in all models, hard coal price has a negative coefficient on simulated and actual hard coal output), with a couple of exceptions. In particular, the coefficient for the emission allowance price is lower in magnitude in the model for lignite generation compared to hard coal generation, although this can be explained by the fact that lignite has a lower marginal cost, and is thus baseline generation that does not respond to changes in input prices. The coefficients for hard coal price in the lignite model are both negative and statistically significant, although smaller in magnitude compared to the hard coal model.

We observe significant geographical shift in generation between our simulation and observed data. We attribute this to the fact that we make all cross-border transmission capacity available in both stages of the market clearing (day-ahead and real-time operation). In the European wholesale market, a large amount of cross-border transmission capacity is not made available in the initial zonal market clearing to accommodate the needs of the intraday market, safety margins and possible redispatch actions. This hypothesis is also supported by the fact that the total magnitude of imports and exports was 8% larger in the simulation compared to observed data. It should be obvious that larger capacities to import and export between countries lead to a lower costs to satisfy system-level load. While our results are sensitive to the assumptions we make about the thermal capacities of transmission lines and marginal costs of generation units, our results can be taken as strong evidence for the fact that more imports and exports between European countries would lower the costs to

operate the European wholesale market. Implementing a nodal market design would very likely allow more cross-border capacity to be made available to the wholesale market, as the need for redispatching is reduced significantly. While the geographical shift in generation may seem large for some countries, the overall change in the magnitude of cross-border trade is not large. This suggests that the geographical shift is driven by a more efficient use of generation assets, and not on inaccurate assumptions about transmission capacity.

Country	observed output (MWh)	simulated output (MWh)	difference (%)
Germany	51,670.82	52,872.07	2.27 %
France	47,932.70	55,122.47	13.04 %
Italy	30,373.73	26,447.58	-14.85 %
Spain	27,421.17	29,698.59	7.67 %
United Kingdom	25,913.62	27,218.17	4.79 %
Sweden	19,728.44	17,692.35	-11.51 %
Norway	17,401.60	17,394.81	-0.04 %
Poland	14,917.05	17,494.28	14.73 %
Finland	10,593.34	8,445.53	-25.43 %
Netherlands	9,090.63	12,417.85	26.79 %
Czech Republic	7,756.35	8,324.95	6.83 %
Belgium	7,712.32	9,045.62	14.74 %
Switzerland	6,203.85	5,422.61	-14.41 %
Austria	6,131.56	7,083.30	13.44 %

Table: Simulated and observed hourly average aggregate country-level output from all generation sources.

5.2 Dispatch costs

One of the key arguments in favour of nodal pricing is the fact that the dispatch in always the cost-minimizing physically feasible dispatch (given that suppliers are not paid less than their bid prices) − we therefore expect that the as-offered cost of the dispatch (the sum of the bid quantities × bid prices) is likely lower than in the as-offered cost observed in the data. This analysis is complicated by the fact that we observe actual aggregate country-level hourly outputs for different fuel types, and we observe actual hourly unit-level generation for only a subset of generation units. While we can simply calculate the as-offered cost of the dispatches yielded by the simulation, we have to estimate the as-offered cost of the actual dispatch. We present different estimates based on different assumptions to investigate the hypothesis that our simulated dispatches exhibit lower as-offered costs compared to observed data.

We estimate the total as-offered cost of the observed dispatches assuming that (i) observed generation is distributed across countries and fuel types exactly as in the simulation, (ii) observed generation is distributed across countries and fuel types according to nameplate capacities of the generation units, and (iii) by calculating the hourly as-offered cost for the subsample of generation units for which we have hourly unit-level generation data:

Estimation strategy	Difference between observed and simulated dispatch cost
(i)	0.9 %
(ii)	-8.7 %
(iii)	-3.0 %

Out of these three assumptions, (i) is obviously the most optimistic, as it is based on our simulated cost-minimizing physically feasible dispatch. Essentially, we assume that if we observe Germany produced in aggregate 100 MWh of electricity using lignite-generated plants at hour t, the average marginal cost of this generation is equal to the quantity-weighted average marginal cost of lignite generation on hour t in our simulation. It is perhaps surprising that this assumption leads to average dispatch costs that are higher in our simulation compared to observed data, but we note that i) due to issues related to redispatching (that we have outlined in previous chapters), TSOs may be unable to obtain a dispatch that minimizes the as-offered cost of generation and ii) the "implied" dispatch we create bya assigning aggregate generation using this method may be actually physically infeasible. We can therefore consider this a sort of an upper bound for the difference between average observed and simulated dispatch costs. Assumption (ii), in turn, should be considered a lower bound. While we could estimate lower and upper bounds by assuming that generation is always fully distributed to the cheapest and most expensive generation units respectively, these bounds would be uninformative and unrealistic, as they would ignore physical feasibility altogether.

The most accurate estimate we obtain for the actual difference between the as-offered costs of observed and simulated dispatches is obtained by comparing the as-offered costs of only those generation units for which we have hourly unit-level output data using our marginal cost estimates. Our result that the as-offered cost is 3 % lower in our simulation compared to actual data is in line with previous literature, which consistently finds similar differences that are between $1\% - 3\%$ (see the literature review in section 2.3). However, as the majority of the difference in the operation cost between a nodal market and a zonal market with market-based redispatch may be caused by redispatch costs (Zarnikau et al. (2014), Aravena & Papavasiliou (2017)), our results are suggest larger cost differences between nodal and zonal pricing than most of the generally cited literature.

5.3 Locational marginal prices

We present average simulated nodal prices over a distribution of days reflecting different supply, demand and fuel price conditions. We also present a distribution of quantity-weighted average prices paid by loads on the country level. We calculate the average price in a country by weighing nodal prices using net withdrawals, i.e., the difference between generation and load, to obtain a country-level average price paid by consumers.

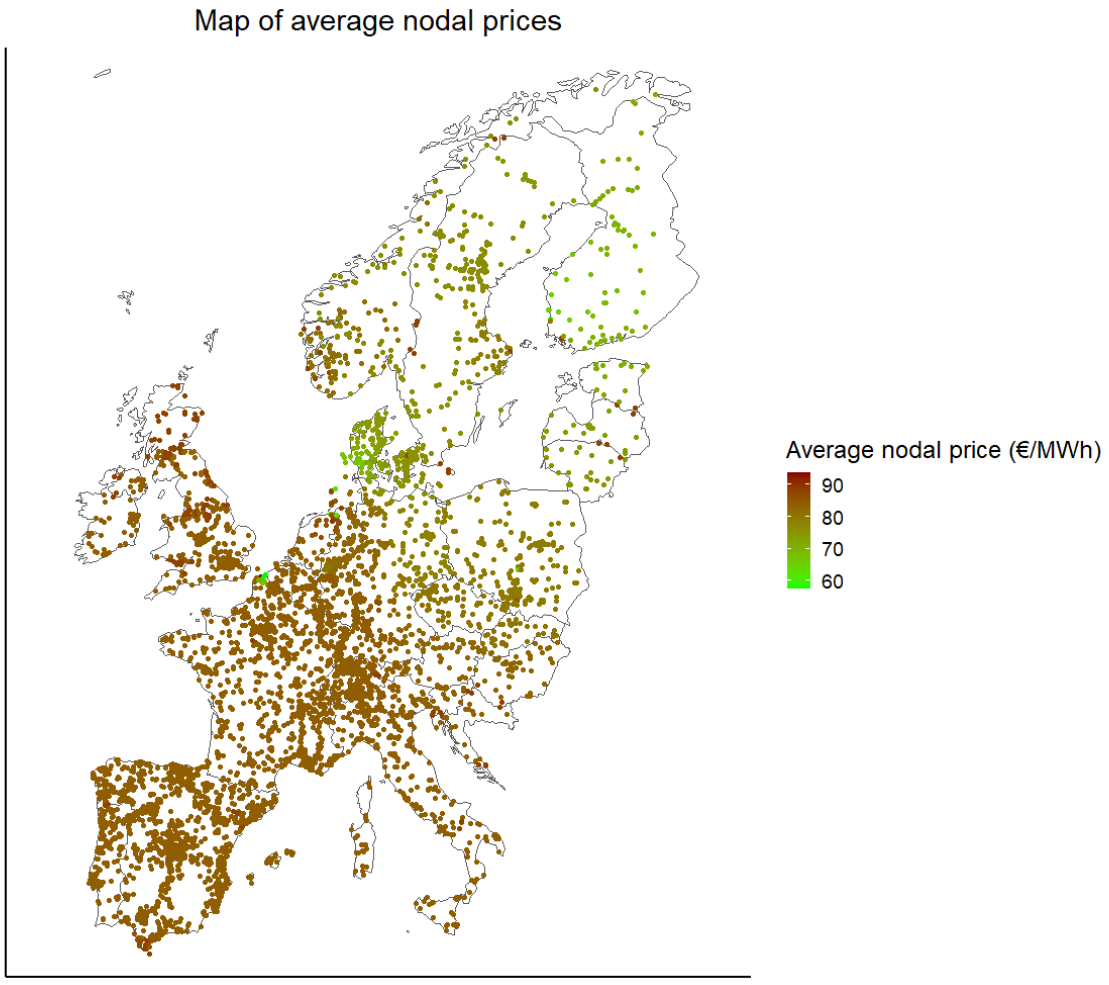


Figure 18: Map of average nodal prices

We notice that there are persistent differences in average nodal prices between countries and within some countries, but they are not very large. Figure 19 compares the distribution of country-level average simulated nodal prices to actual prices in the year 2023. We compare

these hourly average country-level prices to actual country-level wholesale prices for the year 2023 using data from ENTSO-E:

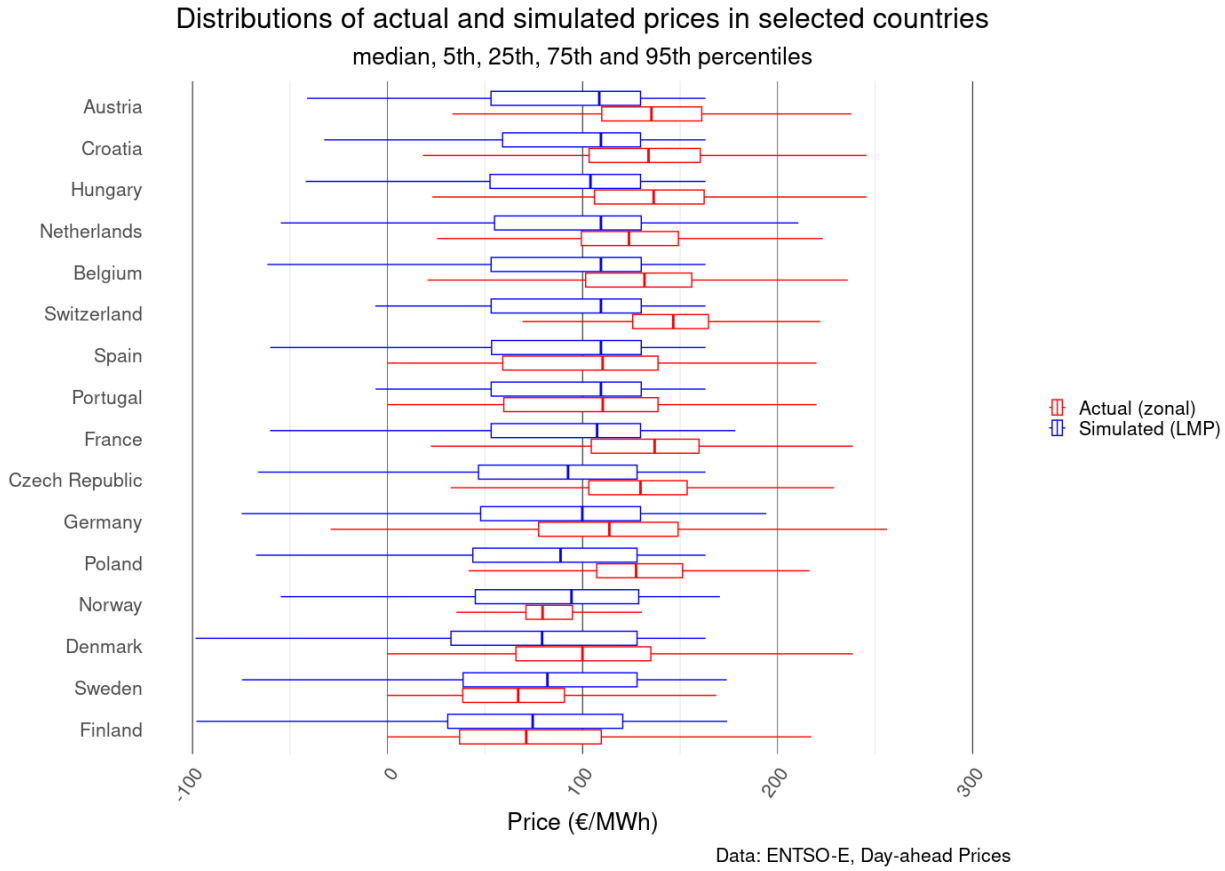


Figure 19: Distribution of country-level average simulated hourly prices (blue) and actual hourly prices from the year 2023 (red). Boxplot distribution ($5\% - 25\% - 50\% - 75\% - 95\%$).

We do not attempt to accurately predict nodal prices under a hypothetical European nodal wholesale market, as our simulation is based on key simplifications. We thus consider the comparison of simulated and actual prices to be more of a robustness check to see if our model produces plausible results. Generally cited results from previously literature find only very modest differences in average prices between a nodal and a zonal wholesale market (see literature review, especially Zarnikau et al. (2014)); and as Hirth & Schlecht (2020) argue, the difference in the operation cost between a nodal market and a zonal market with market-based redispatch is mainly caused by redispatch costs, not necessarily by the prices faced by consumers. We do not thus expect very large differences between the simulated average country-level prices and actual prices, and such differences do not arise in our

comparison (figure 19). For the majority of countries, the average simulated country-level wholesale price is lower than the actual zonal price. This may be due to our assumption of perfect competition (which may be unrealistic) or potential inaccuracies in our transmission constraint assumptions, but it may be partly explained by INC-DEC arbitrage that yields higher average country-level wholesale prices in zonal markets with market-based redispatch compared to a hypothetical *ceteris paribus* nodal wholesale market.

We furthermore calculate the country-level average price paid by loads by taking a quantity-weighted mean of nodal prices (for each hour) using net withdrawals as weights (net injections, i.e., nodes where generation exceeds demand are given weight zero). This gives a more robust measure of the average price that consumers paid for electricity on hour h in country i. This comparison can be found in appendix 5.

We also observe that the simulated price variance between and within countries is driven by a small number of hours with very high variance (figure 20). These hours are furthermore concentrated around certain months, which can be explained by seasonal variation in demand and fuel prices and (probably more importantly) the output from intermittent renewable generation sources. These results highlight the fact that a nodal wholesale market allows different generation sources to be compensated (and consumers to be charged) differently in the minority of hours during which the transmission grid is particularly congested, although for most hours, price variance remains low.

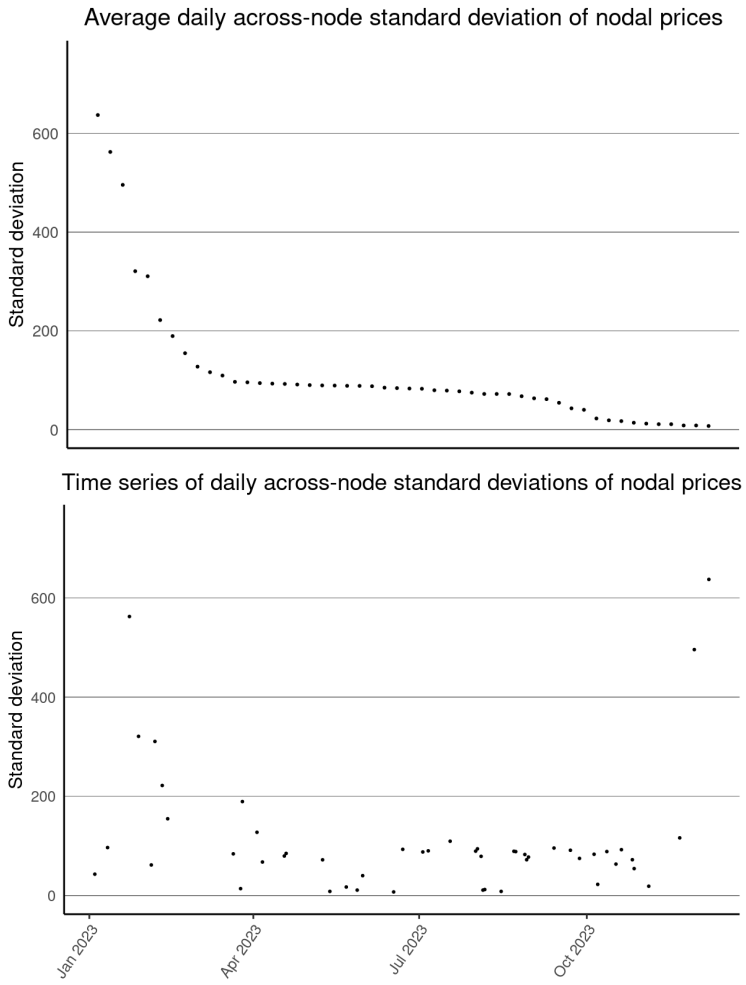


Figure 20: Distribution and time series of average daily across-node standard deviations in hourly nodal prices

The nodal price crucially depends on the congestion in the power grid (as measured by the sum of the shadow prices of transmission constraints), the linear shift factors as well as supply and demand conditions in nodes. Recall that in the absence of any binding transmission constraints (or line losses), all nodal prices are equal to the bid price of the marginal unit in the power system, since the increase in the total cost to satisfy demand caused by an increase in demand in one node is simply the bid price for the marginal generation unit in the system for all nodes. In reality, demand in Finland cannot obviously be served by generation in Spain due to line losses[13]. While the effect of bottlenecks on prices in our

[13]We account for line losses by restricting the number of nonzero shift factors for nodes, which essentially restricts the geographical scope of generation that can serve demand in a particular node

model might seem predictable and straightforward, this is not the case. It might seem intuitive that a bottleneck between, say Finland and Estonia, would split these two countries into two zones with two different prices. In reality, however, this binding transmission constraint would be (very likely) reflected into all nodal prices in Finland and Estonia slightly differently. Recall that the formula for the congestion element of the nodal price in node i is a weighted sum of all transmission constraint shadow prices, weighted using row i of the shift factor matrix. Since the shift factors corresponding to transmission element k are different for different nodes (even two neighbouring nodes), binding transmission constraints will be reflected slightly differently on all nodes for which the corresponding shift factor is nonzero. This point might seem minute, but it is very important for interpreting the analysis of average nodal prices that will follow. Price differences across nodes arise from binding transmission constraints for the following reason: if the grid is congested, increasing load in node i requires the generation in other nodes around node i to change to offset the implied increase of flow on the congested transmission element.

With this in mind, it is easy to understand the mechanism through which a nodal wholesale market compensates generation units based on how important they are to achieving a cost-minimizing physically feasible dispatch. Since the implied cost of increasing load in node i depends on the cost of generation in the nodes around node i where the dispatch has to change to accommodate the increase in load, the alternative is to simply increase generation in node i to meet the increase in load (which does not require a change in the dispatch at other nodes, as power balances do not change as a result). Generation units in nodes with a high average nodal price are therefore more important to achieving a cost-minimizing physically feasible dispatch than generation units in nodes with a low average nodal price. Higher average nodal prices will attract new investments in generation in nodes where it will contribute more to achieving cost-minimizing physically feasible dispatches, and lower average nodal prices will likewise attract more loads where they will contribute to the same objective.

These factors imply that the nodal price can be considered a measure of how important the generation resources in a particular node are needed to satisfy demand in a physically feasible and cost-minimizing dispatch. Importantly for new investments, the nodal price is thus a mechanism that rewards generators depending how much they are needed for the cost-minimizing and physically feasible dispatch.

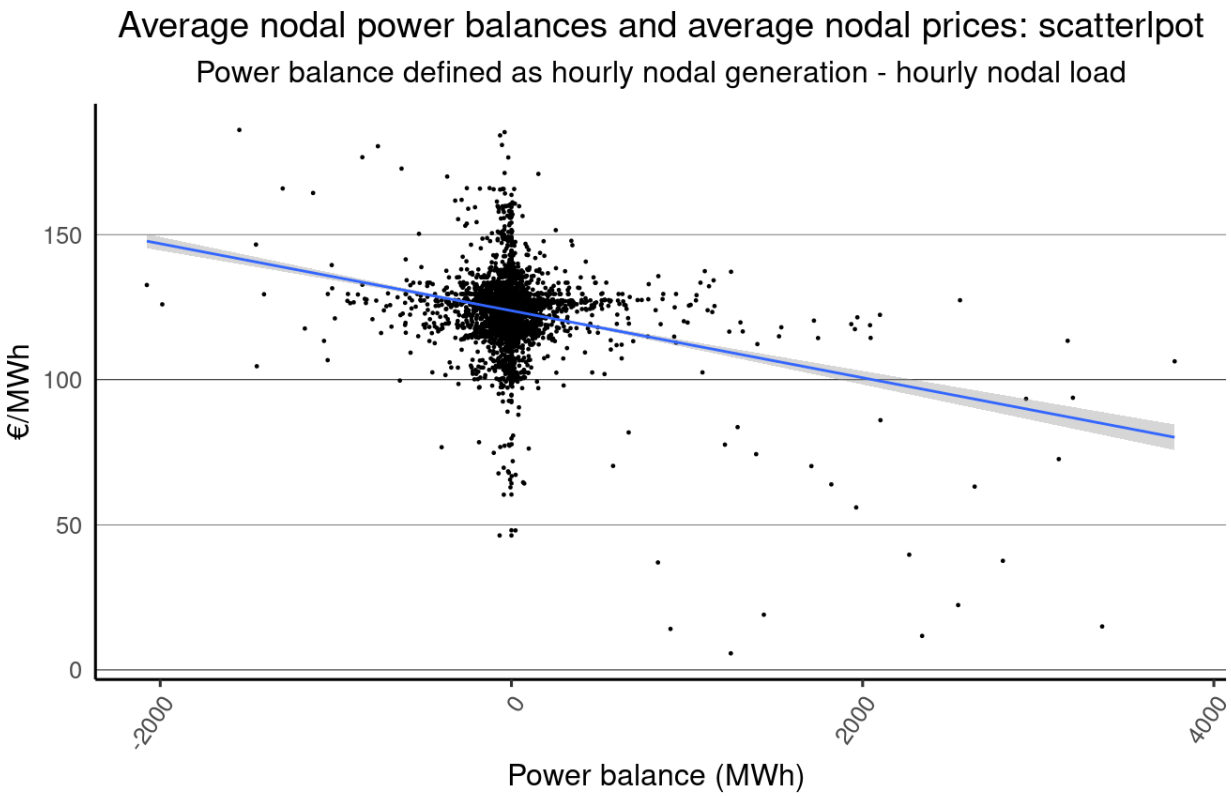


Figure 21: Correlation and trend line between average nodal prices and nodal power balances (defined as the difference between aggregate generation from all generation units and load in node n)

Figure 21 plots the correlation between nodal prices and nodal power balances. This result suggests (predictably) that nodes with an excess of generation will result in a lower nodal price. In other words, nodes that on average import large amounts of electricity have larger nodal prices and nodes that export electricity have lower nodal prices. While transmission infrastructure has been built to sustain a power system where large generation resources can be located away from large population centers (with a large demand for electricity), generation resources in areas and nodes with large generation surpluses do not to contribute to to achieving a cost-minimizing physically feasible dispatch as much as generation resources in areas and nodes with large demand surpluses. This fact is of considerable relevance for public interest concerning new investments in generation resources. For example, regions with high wind and solar power potential may be situated far away from large population centers and concentrations of industry. If the amount of electricity paid to generators is equal across a large pricing zone, renewable entrants will primarily consider the wind/solar potential at different locations when deciding the location of their investment (aside from possible costs

from building transmission infrastructure). Allowing prices to vary across nodes creates price signals that guide investments to the socially optimal location.

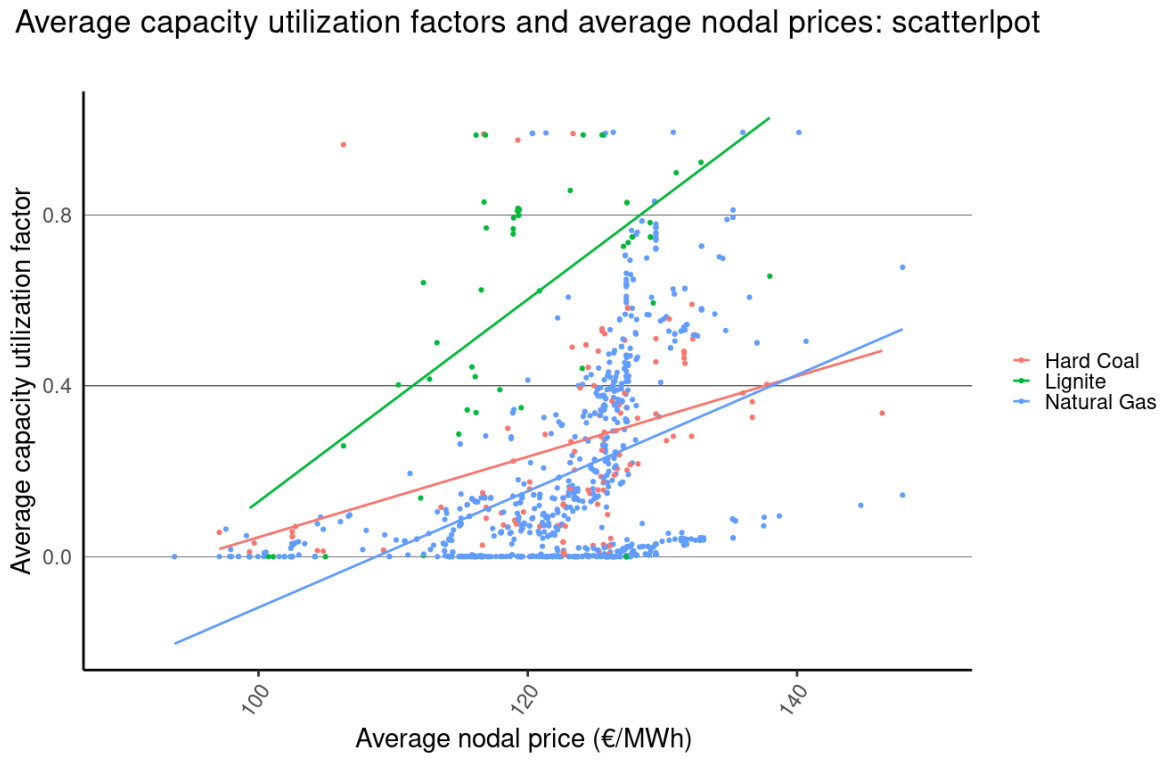
5.4 Capacity Utilization

Country	Hard Coal	Lignite	Natural Gas
Germany	40.2 %	62.9 %	17.1 %
Croatia	33.4 %		18.7 %
Poland	25.9 %	36.4 %	31.5 %
Czech Republic	22.6 %	82.5 %	4.3 %
Spain	22.3 %		17.5 %
Italy	13.5 %		31.3 %
Hungary	7.2 %	34.9 %	9.4 %
Slovakia	3.7 %	50.6 %	9.7 %
Slovenia		71.4 %	6.5 %
Belgium			20.9 %
United Kingdom			13.9 %
Austria			11.7 %

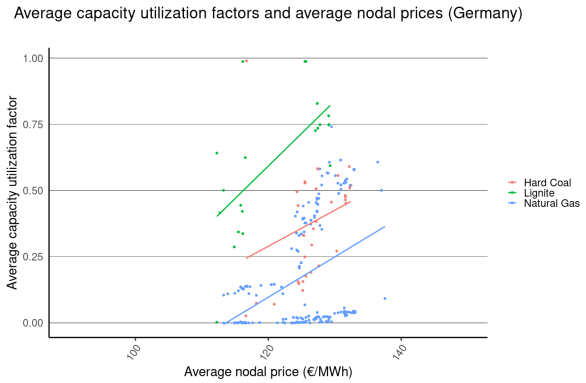
One of the key results of our simulation are persistent differences of the utilization of generation resources within countries or pricing zones. The current European power system has been shaped by decades of zonal pricing, whereby private investment decisions account for shift factors and grid congestion only insofar as it affects the INC-DEC game. The perverse incentives this creates are discussed in Hirth & Schlecht (2020). The TSO ensures free competition inside a pricing zone by clearing the market based on the merit order of generation units, which implies that all generation units are equally considered regardless of location within the pricing zone. In a nodal market, however, not all generation units within countries are equal. The objective is to minimize the cost of meeting demand while creating a physically feasible dispatch. The nodal market optimization is not based on the country-level merit order, and it follows that the dispatch may involve unit i in node k with a bid of p_i being assigned to generate, while assigning unit j in node n with a bid p_j not to generate even though nodes k and n are in the same country.

The key aspect of the optimal dispatch in a nodal market is that units that are needed to satisfy demand in a cost-minimizing dispatch receive higher average nodal prices (and are cleared to generate more). It follows that systematic differences in the utilization of generation resources and nodal prices within countries may arise. While this kind of outcome may be considered undesirable, it reflects the long-term consequences of a mismatch between the

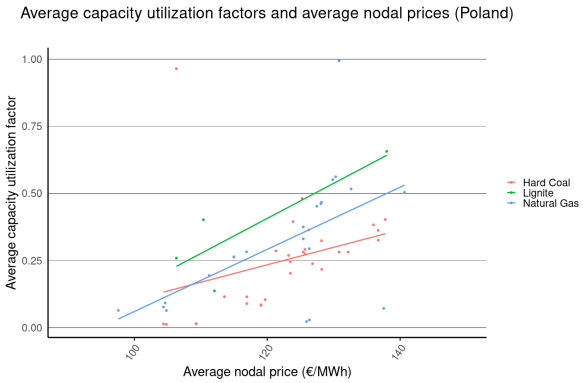
actual power grid and the power grid model used in pricing. The obvious implication of this is that a nodal market incentivizes investments to locations where generation is needed more to satisfy demand in a cost-minimizing dispatch (i.e., where socially optimal) and disincentivizes investments to locations where generation is needed less to satisfy demand in a cost-minimizing dispatch (i.e., not socially optimal).



(a)



(b)



(c)

Figure 22: Joint distribution of average nodal prices and average capacity utilization factors for lignite, hard coal and natural gas power plants in the entire simulation area (a), Germany (b) and Poland (c)

Our simulation shows considerable differences in the utilization of fossil-fired generation resources within countries. The differences are caused by the fact that generation units in

different areas of countries contribute to achieving a cost-minimizing physically feasible dispatch differently (depending on how they are situated in the transmission network, and thus how network flows are affected by their output). As we have outlined in previous sections, nodal pricing is a mechanism through which different generation units receive different compensation based on their contribution to the cost-minimizing physically feasible dispatch. This mechanism is market-based and transparent in the sense that the nodal price in node n is equal to the reduction in the system-wide cost of satisfying demand caused by a one-unit increase in generation in node n. All units are rewarded according to their contribution to the objective of achieving a cost-minimizing physically feasible dispatch. An important observation is that the regional differences in capacity utilization we obtain from our simulation likely already exist, although we cannot observe them from aggregate country-level output data. These regional differences are caused by physical feasibility constraints, which must be respected regardless of the structure of the wholesale market. In the current European zonal wholesale market, generation units in export-constrained regions and nodes may have to be DEC-ed, and generation units in export-constrained regions may have to be INC-ed. This likely results in similar regional differences in capacity utilization to those we see in our simulation, with important differences. In particular, even though congestion management can be market-based (much like nodal pricing), it allows market participants to arbitrage the difference between the (zonal) market-clearing price and the (nodal) redispatch price. These arbitrage opportunities exist for generation units in both export-constrained and import-constrained regions and nodes. Thus, market-based redispatch rewards both generation units that are likely to be DEC-ed (units with low capacity utilization) as well as units that are likely to be INC-ed (units with low capacity utilization), whereas nodal pricing systematically rewards units that contribute more to achieving a cost-minimizing physically feasible dispatch (the units that exhibit higher capacity utilization factors), as seen in figure 22.

For intermittent renewable generation units (solar and wind), we set the lower bound for output to zero. While this might not accurately reflect the intermittent nature of these generation units (although wind power generation units can be turned off, and indeed have to be turned off when wind speed exceeds a certain limit), we mainly do this to investigate whether there is excess capacity of renewable generation in some nodes, in the sense that it would be cheaper to not produce at full capacity for some renewable generation units, despite the assumptions that these units bid at negative prices. We find that out of all nodes with renewable generation capacity, 4 % had an average capacity utilization factor less than 99%, and 1% of nodes had had an average capacity utilization factor less than 95%. This 1% of units are mainly very large concentrations of offshore wind turbines in the Netherlands, Belgium, Germany and France. We acknowledge that these results might be caused by inaccuracies in our data on the transmission system that might not accurately reflect the large transmission capacity required to connect these concentrations of wind turbines to the grid,

or alternatively the fact that we do not incorporate a demand response in our model. We furthermore acknowledge that our method of distributing observed country-level generation may result in inaccuracies, as different regions have systematically different levels of wind and solar power potential, which is not captured by the nameplate capacity of units, which we use to distribute demand across units. However, we point out that large concentrations in any kind of generation have effects on line flows in the surrounding nodes (even in nodes far away from the concentration), which may cause costly congestion. Assuming this is the case, and the results are not caused by potential inaccuracies in our model, we find a slight oversupply in offshore wind in a few nodes in Northwestern Europe.

For nuclear generation units, we likewise set the minimum output to be less than the observed unit-level generation. We find that the average capacity utilization of nuclear generation units was less than 0.99% only in Spain, where the average capacity utilization was 98%. We do not thus find systematic oversupply of nuclear generation.

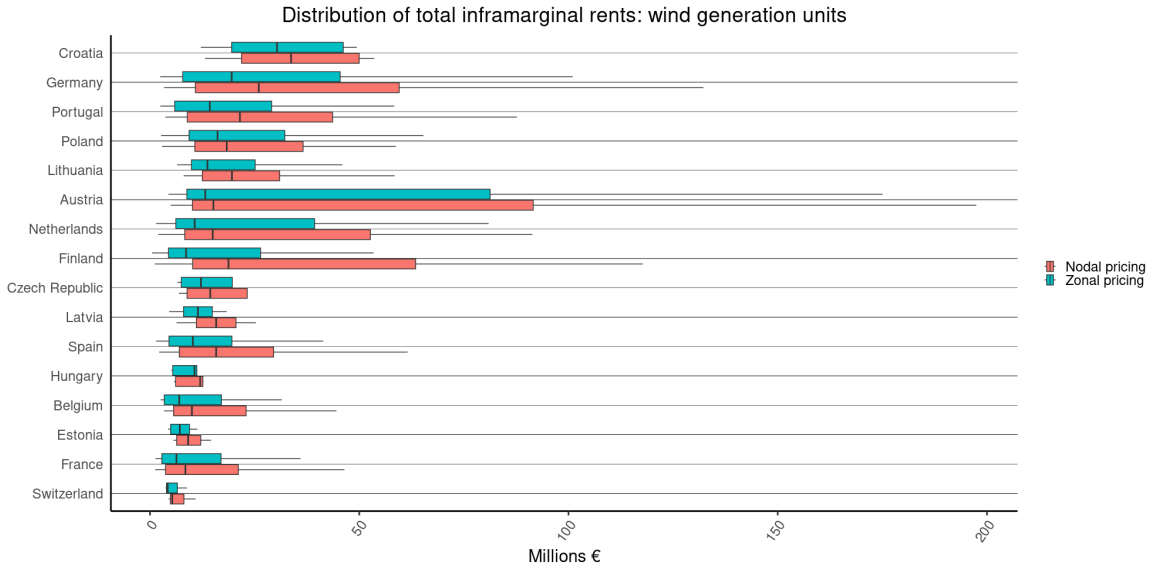
5.5 Producer surplus

As we have outlined in previous sections, allowing prices to vary across nodes changes investment incentives compared to a wholesale market that uses zonal pricing. As shown in section 5.2, our simulation yields persistent differences between nodal prices within countries, which in turn yields differences in the producer surpluses of generation units located in different nodes and regions. This is the key mechanism through which nodal pricing may incentivize investments in generation units in nodes where they will have a positive contribution to achieving a cost-minimizing physically feasible dispatch. For intermittent renewable generation units with static marginal costs, this producer surplus is simply the difference between the static marginal cost and the relevant nodal price. The fact that intermittent generation resources have marginal costs that are lower than wholesale prices for the vast majority of hours leads to their producer surpluses to be labelled as inframarginal rents[14]. Similar inframarginal rents obviously exist for other types of generation, including all non-marginal fossil-fired generators with positive outputs. In a nodal wholesale market, however, the nodal price is not necessarily equal to the marginal unit in the node, since the nodal price is fundamentally a weighted average of the marginal costs of other units in the system. We still use this terminology as it is standard in the field.

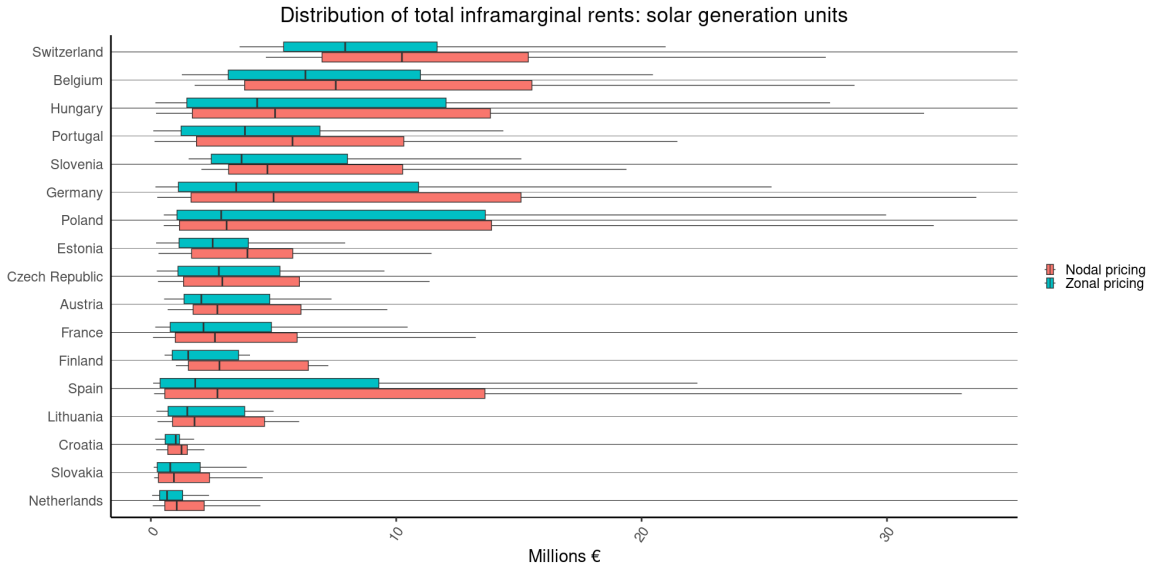
We compare the inframarginal rents that generation units obtain in our simulation and in the observed data. First, we observe that solar and wind generation units seem to ob-

[14]since these units are almost always inframarginal, i.e., their bid prices are below those of the price-setting (marginal) unit

tain consistently slightly higher total inframarginal rents in our simulation when compared to actual price data from the zonal wholesale market. This may seem like an unexpected result, but we refer to figure 21 (which shows a negative relationship between average nodal net balances and average nodal prices), and the fact that these units are less concentrated to large generation nodes, and are in fact often located close or in to large consumption nodes where nodal prices are consistently above average, from which it follows that these generation units can in fact be expected to obtain higher total inframarginal rents under nodal pricing compared to zonal pricing. In other words, these renewable generation units do not form concentrations that are large enough to cause major local downward pressure in nodal prices. Perhaps the more interesting observation is the fact that the variance in total inframarginal rents is higher in our simulation compared to actual data. This is an important desirable property of nodal pricing, which leads to generation units (especially intermittent renewable units) to be compensated differently within countries. This result supports our hypothesis that nodal pricing would create price signals that incentivize investments in renewable generation units in the nodes where they will have a larger contribution to achieving a cost-minimizing physically feasible dispatch.



(a)

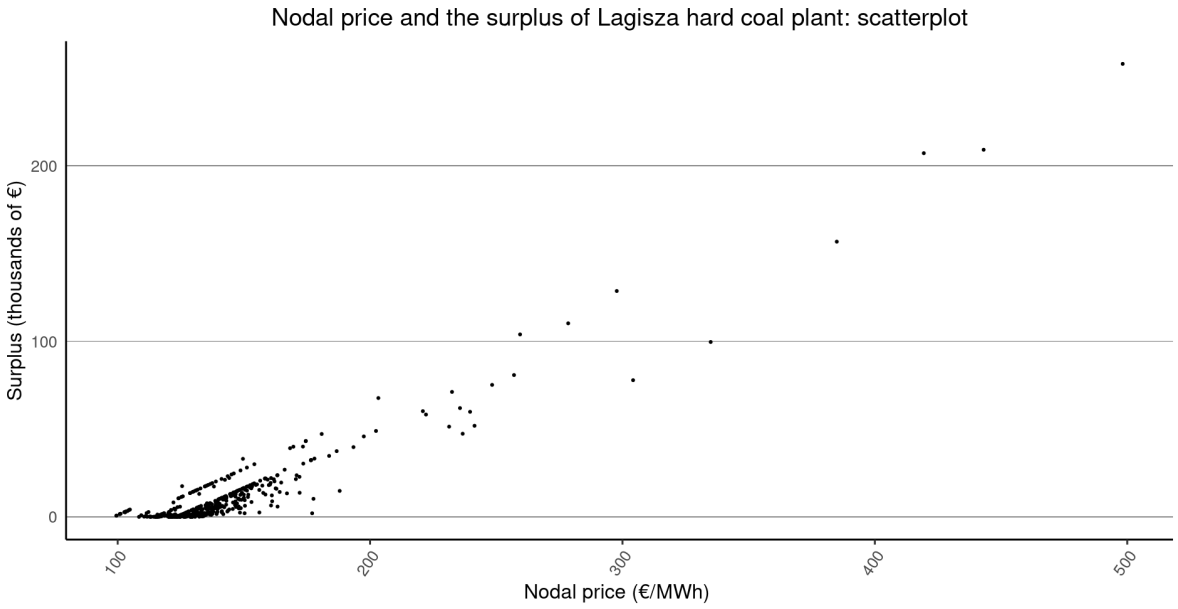


(b)

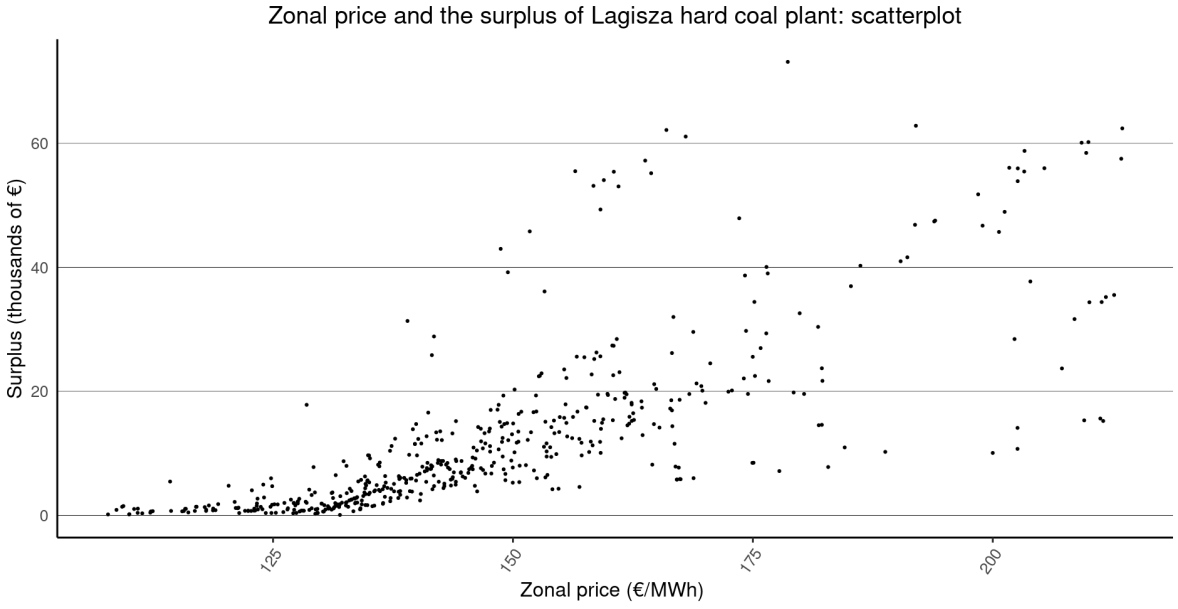
Figure 23: Distribution of total yearly inframarginal rents for (a) wind generation units and (b) solar generation units in our simulation (extrapolated from our sample of 50 days) and calculated from observed data from zonal prices.

As we show in figure 20, the distribution of hourly system-wide standard deviations of nodal prices resembles a Pareto distribution, with a small number of hours exhibiting a very

large variance, and the majority of hours exhibiting low variance. This is particularly relevant for fossil-fired generation units that are marginal for the majority of hours, and make most of their profits on a small number of hours. We consider the example of Lagisza power plant, a hard coal generation unit in Poland. We calculate hourly surpluses using actual data on generation and zonal prices and our marginal cost estimates, and hourly surpluses using data from our simulation. We see that under nodal pricing, large outliers represent a larger share of total producer surplus compared to zonal pricing. In particular, the generation unit analyzed obtains half of its profits in 4 % of the hours in a year in our nodal pricing simulation, whereas under zonal pricing, it obtains half of its profits in 7 % of hours in a year. This is an expected property of nodal pricing, as concentrations of fossil-fired generation may pressure nodal prices around the concentration downwards, which in turn may reduce the number of hours where the unit makes a profit. Conversely, local cost and demand shocks may exert upwards pressure on nodal prices that under zonal pricing would have less of an impact on individual plants. The share of hours where the plant we analyze makes a profit is 42 % under nodal pricing and 46 % under zonal pricing.



(a)



(b)

Figure 24: Joint distribution of (a) hourly nodal prices and surpluses, calculated using resutls from our simulation and (b) hourly zonal prices and surpluses, using actual data on generation and zonal prices and our marginal cost estimates.

A comparison between the surpluses of fossil-fired generators between our simulation and the observed data is complicated by the fact that we only have access to unit-level generation data for a subsample of generation units. Furthermore, we notice that the observed generation of generation units is positive on some hours for which we estimate the marginal cost to be higher than the zonal price. While this may be caused by redispatch actions, it may be that our marginal cost estimates are not accurate for some plants on some days. We thus do not attempt to calculate differences in the surpluses of fossil-fired generation between our simulation and observed data, as these results would likely be somewhat inaccurate. We do note that the share of hours on which generation units operate is on average higher in the observed data compared to our simulation[15], which we consider tentative support for our hypothesis that under nodal pricing, fossil-fired generation units obtain a larger share of their surplus on a small number of high-price hours:

Fuel type	Simulation	Observed data
Hard Coal	45.1 %	70.0 %
Lignite	82.8 %	82.0 %
Natural Gas	38.0 %	51.0 %

Share of hours on which generation is nonzero (actual generation data from ENTSO-E, results from simulation)

Finally, we recreate figure 25 using average inframarginal rents instead of average nodal prices. We confirm that units that contribute more to achieving a cost-minimizing physically feasible dispatch (and are thus cleared to produce more compared to units that do not contribute as much to this objective) obtain higher average inframarginal rents:

[15] this is a proxy for whether the marginal cost of generation is higher than the wholesale price, although redispatch actions lead units to generate even when their marginal cost is higher than the wholesale price

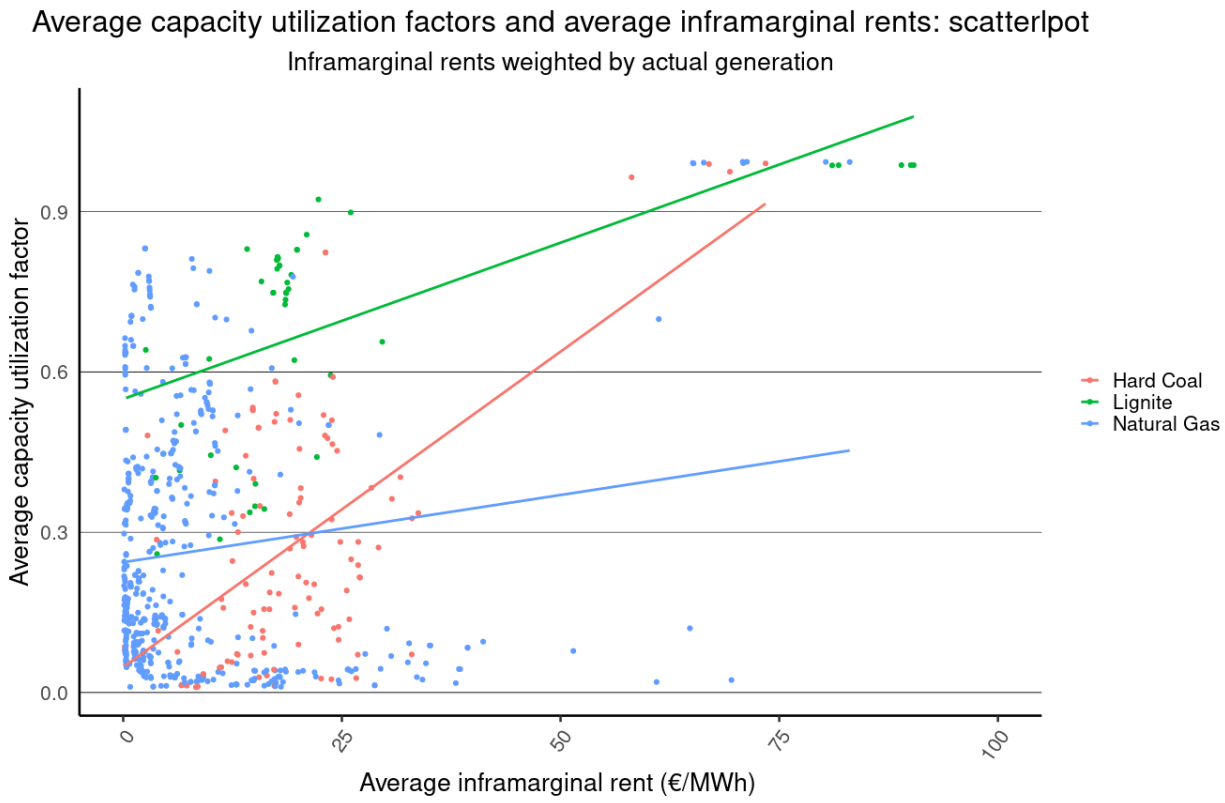


Figure 25: Average inframarginal rents and capacity utilization factors: scatterplot

While market-based dispatch and INC-DEC arbitrage may yield somewhat similar differences in surpluses to generation units, we do not have detailed data on redispatch actions or the redispatch payments to generators, and we cannot thus say anything about which units receive redispatch payments and how they are compensated in our simulation

5.6 Emission effects

Differences in total emissions between our simulated dispatch and actual data may arise from both the intensive margin and the extensive margin. Our analysis on the differences in emissions between our simulation and actual data is complicated by the fact that we observe unit-level hourly generation for only a subsample of generation units. We use the same data we use to estimate unit-level marginal costs to estimate marginal emission factors for all fossil-fired generation units in our model, which allows us to calculate the total emissions caused by the operation of these units in our simulation.

To better address possible intense-margin effects, we use the hourly unit-level genera-

Fuel type	simulated generation (TWh)	actual generation (TWh)	% difference
Hard Coal	166.1	156.6	6.1%
Lignite	134.5	147.9	-9.1 %
Natural Gas	459.9	441.8	4.1 %
Fuel type	simulated emissions (millions TnCO2)	actual emissions (millions TnC02)	
Hard Coal	142.8	131.2	
Lignite	131.1	145.2	
Natural Gas	195.4	187.9	

tion data (Entso-E transparency platform, observed generation per generation unit) we have from a subsample of fossil-fired units included in the simulation. Our generation unit data contains different types of generation units (for both natural gas and coal), which have different technical characteristics and thus different marginal emissions. Comparing actual hourly outputs and simulated outputs for the subsample of generation units, we observe differences between actual data and our simulated data. In particular, we observe that the actual output from generation units with higher marginal emission factors is higher in some countries and for some fuel types in the observed data compared to our simulation. In other words, our simulation yields "cleaner" dispatches for all fuel types when comparing the units in the subsample for which we have actual hourly output data. We then estimate implied country-level average marginal emission factors for lignite, hard coal and natural gas generation for actual data and simulated data and compare the results. We observe that using these marginal emission factors, our simulation results in total emissions that are about 1% lower compared to observed data, despite the fact that the output from fossil-fired generation units was higher in our simulation (see table below). 73 % of this difference is caused by the differences in the operation of natural gas units and 19 % is caused by the differences in the operation of lignite units.

Fuel type	simulated emissions (millions TnCO2)	actual emissions (millions TnC02)
Hard Coal	142.8	131.9
Lignite	131.1	146.9
Natural Gas	195.4	194.8

Furthermore, we notice that the the standard deviation of the output from natural gas plants is consistently higher in the observed data (on the sample of days that we solve the model for) compared to the simulation. This is also relevant for carbon dioxide emissions. Combined cycle natural gas plant must generally run sufficiently close to nameplate capacity to be able to produce in combined cycle mode[16]. Combined cycle mode also requires a longer

[16]a combined cycle unit can generally produce in both combined cycle mode or open cycle mode. In combined cycle mode, exhaust gases from the combustion of natural gas (first cycle) are used in a second

start-up and ramping time compared to open cycle mode. A high variance in the output of combined cycle gas units or low capacity utilization thus results in less overall thermal efficiency, as more fuel is needed to produce compared to the optimal operation of the units. We analyze hourly plant-level generation data for combined cycle gas plants (ENTSO-E) and observed yearly emissions (EU-ETL emissions trading database) and find i) a positive relationship between the standard deviation of capacity utilization and yearly carbon dioxide emissions and ii) a negative relationship between the average capacity utilization and yearly carbon dioxide emissions. We then regress the implied emission factor (calculated using observed hourly generation and yearly emissions data) on i) the average capacity utilization factors and ii) the standard deviation of capacity utilization factors for the combined cycle gas units in our sample using the age of the unit as a control variable. We find statistically significant effects in both models. If our results are robust and nodal pricing indeed reduces the variance in the output of combined cycle gas units compared to zonal pricing with large-scale redispatch, we can conclude that adopting nodal pricing may reduce the carbon dioxide emissions from natural gas units. We also point out that combined cycle gas units are likely targets of redispatch actions due to the inherent flexibility of natural gas, and the fact that they represent about $83\% - 86\%$ of all natural gas units in Europe. These redispatch actions can cause undesirable variation and low capacity utilization which leads to lower thermal efficiency and higher carbon dioxide emissions.

In our analysis of the EU-ETL emissions trading data, we find that a 0.1 increase in the standard deviation of capacity utilization is associated with a 0.01 increase marginal emissions (measured in tonnes of CO2/MWh). We also find that a 0.1 increase in average capacity utilization is associated with an 0.004 increase in marginal emissions. We observe a 22 % reduction in the standard deviation of capacity utilization, which implies that there is signifficantly less variance in our simulated unit-level output. A very simple back-of-the-envelope calculation suggests that the average marginal emissions for the natural gas units in our simulation are thus about 0.37 tnCO2/MWh (compared to the 0.38 we observe in our analysis of the EU-ETL data). Based on this estimation, our simulated annual emissions from natural gas are actually 190.1 millions TnCO2 instead of 195.4 millions TnCO2. We consider this very tentative evidence of a possible effect, and do not place much weight on this result. The magnitude of this effect is around 1 % of total annual emissions. More details about this analysis can be found in appendix 4.

We conclude the analysis of carbon dioxide emissions by emphasizing that our results do not offer very strong evidence to show that implementing nodal pricing will necessarily lead to lower carbon dioxide emissions compared to zonal pricing. However, we also note that the

cycle to generate more electricity, which increases the overall efficiency of the power plant. In open cycle mode, these exhaust gases are released after the first cycle.

actual dispatches we observe in 2023 are not only yielded by zonal pricing, but zonal pricing with large-scale redispatch. As we have outlined before, zonal pricing with multiple independent TSOs performing large-scale redispatch simultaneously and with little coordination can be expected to lead to the inefficient use of generation resources. The redispatching process we observe in Europe may result in TSOs being unable to INC and DEC the units that would result in the cost-minimizing due to the INC-DEC game and the lack of coordination of redispatch actions. Our marginal cost estimates show that within individual fuel types, less polluting generation units have lower marginal costs of production due to carbon pricing and more efficient fuel use (i.e., lower heat rates).

6 Conclusion

We have estimated the potential effects of implementing a larger level of spatial granularity in the European wholesale market for electricity, which in turn allows all network operating constraints to be included in the market model used to set prices and dispatch quantities. We find that the aggregate energy mix (simulated based on actual input prices and renewable energy output from the year 2023) does not differ significantly from the actual energy mix observed in 2023. We find that aggregate output from natural gas and hard coal units is slightly higher in our simulation compared to observed data, and the output from lignite units is slightly lower, We find a 8 % increase in the total aggregate magnitude of cross-border imports and exports, which increases the efficiency of serving load. We suggest that this result is partly driven by the fact that a nodal wholesale market would require less cross-border capacity to be withheld from the day-ahead market for the purposes of redisaptching. We also find that the total as-offered costs of our simulated dispatches are 3 % lower compared to the as-offered costs of actual dispatches observed in 2023, which we estimate using our marginal cost estimates and different assumptions, in line with previous literature. We find that our simulation yields slightly higher outputs from fossil-fired generation sources compared to observed data, but we estimate that the emission intensity in our simulation was lower compared to observed data (again estimated using different assumptions on the distribution of country-level generation across different plants and our marginal emission estimates), partly due to lower output from lignite and higher output from natural gas, and partly due to changes in the operation of individual generation units. We also find less variance in the output from natural gas units, which may result in lower emission intensities. Finally, we highlight the fact that we compare dispatches yielded by an optimal dispatch model that allows prices to vary across nodes to dispatches yielded by a zonal market (that does not allows wholesale prices to vary across nodes) with large-scale redispatch. The actual dispatches observed in the year 2023 thus reflect a large amount of uncoordinated redispatch actions that are potentially abused by market participants that play the INC-DEC game.

If our assumptions about the marginal costs, operating constraints and the properties of the transmission network are correct, the difference between our simulated dispatches and the actual dispatches is the inefficiency caused by this large-scale redispatch. The average differences between the as-offered costs between the two dispatches are modest and in line with previous literature.

We find that average country-level simulated prices were close to actual zonal prices for most countries − confirming that our results are plausible − but lower for most countries, which is in line with previous literature. We however also find that inframarginal rents paid to intermittent renewable generation units were slightly higher in our simulation compared to actual data, with clearly more variance. This reflects the fact that introducing a larger amount of spatial granularity in the pricing of electricity allows generation resources in the same countries and regions to receive different compensation, depending on their contribution to achieving a cost-minimizing physically feasible dispatch. We thus confirm that nodal pricing would likely create price signals that incentivize investment in the socially optimal location. We find that loads in importing nodes and generators in exporting nodes would very likely be the losers of introducing a larger amount of granularity in pricing. While this has very important implications for the political and regulatory feasibility of such a policy, we do not go into details on this question.

To ensure that our simulated results are comparable to actual data, we simulate the outcomes of a hypothetical Europeran multitisettlement nodal market using a two-stage optimization mechanism. In the first stage, we solve the economic dispatch model using forecast data on demand and the supply from intermittent renewables. In the second stage, we solve the economic dispatch model using realized data on demand and the supply from intermittent renewables, and only allow the fossil-fired units that were dispatched in the first stage to be used. We acknowledge that our simulated dispatch quantities may not reflect all possible factors that would affect market outcomes in a hypothetical European nodal day-ahead market, and our results should not be understood as an accurate prediction of outcomes in a hypothetical European multisettlement LMP market. We use key simplifications to distribute load and renewable output across nodes, and we do not consider the potential effects of factors such as market power or combined heat and power (CHP) generation. All data used in our model was gathered from open sources, notably ENTSO-E. More accurate results could be obtained if we had access to spatially disaggregated data on demand bids, a more detailed model of the European power grid, including information about distribution networks connected to the main grid, or more detailed data on the distribution of solar and wind power generation. Future work based on these results could potentially incorporate market power and imperfect competition using the framework in Wolak (2015), i.e., use data on simulated transmission congestion under the assumption of perfect competition to create a residual demand curve realization distribution and find profit-maximizing strategies for

generators.

Finally, we conclude that the complexity of our model (which is comparable to market models used in US electricity markets in terms of the number of nodal prices and operating constraints involved in the optimal dispatch model) is manageable; we are able to solve our model for one day in approximately 20 minutes using a high-performance computer. In particular, we hope to demonstrate that a hypothetical multisettlement nodal market in Europe would likely not be too complex or burdensome to operate.

Appendices

Appendix 1

Consider a three-node transmission grid where:

- the level of demand in node 3 is 750 MW and 0 MW in other nodes
- Each node has one generation unit s.t. $MC_1 = 80, MC_2 = 100, MC_3 = 200$ and $\max_{Q_1} = 200, \max_{Q_2} = 1000, \max_{Q_3} = 1000$. Marginal costs are expressed in €/MWh.
- The transmission lines have the following capacities: $l_{1\to2} = 100MW, l_{1\to3} = 400MW, l_{2\to3} = 600MW$,

All generation units have a minimum output of 0 MW and bid all available capacity at their marginal cost. We find that the optimal physically feasible dispatch (solved using the standard LMP formula in section 4) is $Q_1 = 200, Q_2 = 500, Q_3 = 50$, and the total as-offered cost of satisfying demand is 76 000 €.

Consider the same optimal dispatch problem without taking into account physical feasibility constraints. This corresponds to a scenario where all nodes in the system are inside the same pricing zone. Optimal dispatch is now $Q_1 = 200, Q_2 = 550, Q_3 = 0$ and the price is 100 €/MWh, but since power flows are $l_{1\to2} = -116.666...MW, l_{1\to3} = 316.666...MW, l_{2\to3} = 433.333...MW$,, the dispatch is physically infeasible. The only way to achieve a physically feasible dispatch is to adjust the output of unit 2 downward by 50 MW and adjust the output of unit 4 upward by 50 MW. Using the "standard" market-based redispatch strategy involves paying unit 3 its as-offered cost for the electricity supplied, and paying unit 2 the market-clearing price for the amount by which its generation is adjusted downward. The initial as-offered cost of satisfying demand is 75 000 €, but the cost of redispatch brings this up to 76 000 €.

The key observation is that the dispatch that minimizes the as-offered cost of satisfying demand is the solution to the nodal optimization problem (as presented in section 4.1); any other dispatch cannot therefore be the cost-minimizing dispatch. While the TSO can utilize ad-hoc adjustments to the initial zonal dispatch in order to achieve a physically feasible dispatch, the final dispatch in a zonal pricing market is not cost-minimizing if it is not the solution to the nodal pricing optimization problem. The methods TSOs use to achieve a physically feasible dispatch are not always perfectly transparent, but it is likely that the methods used are based on heuristic rules and algorithms that minimize the cost of congestion management, but do not necessarily result in the cost-minimizing dispatch. It is likely that zonal dispatch with congestion management does not achieve the cost-minimizing physically feasible dispatch due to several factors:

- If the TSO employs market-based redispatch, generation units may anticipate redispatch actions and arbitrage the wholesale price and the redispatch price (INC-DEC game)
- In the European context, multiple TSOs perform redispatch independently and simultaneously. The redispatch of one TSO affects line flows in the areas under other TSOs, which may complicate achieving the "optimal" redispatch, such that the cost of redispatch is minimized.
- In complex transmission networks, TSOs may be forced to use heuristic rules to determine redispatch actions, which may not result in an optimal redispatch.

Appendix 2

Table 2

	Dependent variable (aggregate hard coal generation):		
	Simulated output	Actual output	Observed - simulated output
	(1)	(2)	(3)
Hydro	−0.115*	−0.231***	−0.116*
	(0.060)	(0.013)	(0.060)
Nuclear	0.124	−0.261***	−0.385***
	(0.099)	(0.022)	(0.099)
Solar	−0.121***	−0.236***	−0.115***
	(0.035)	(0.008)	(0.035)
Wind	−0.047*	−0.207***	−0.160***
	(0.028)	(0.006)	(0.028)
Demand	0.077***	0.214***	0.137***
	(0.029)	(0.006)	(0.029)
P_{EUETS}	−203.123***	−111.842***	91.281*
	(50.007)	(11.075)	(50.007)
$P_{NaturalGas}$	1,649.716***	295.490***	−1,354.226***
	(102.093)	(22.609)	(102.093)
$P_{HardCoal}$	−384.333***	−44.229***	340.104***
	(53.343)	(11.813)	(53.343)
Observations	493	493	493
R^2	0.906	0.985	0.683
Adjusted R^2	0.904	0.985	0.678
Residual Std. Error (df = 485)	9,991.238	2,212.652	9,991.221
F Statistic (df = 8; 485)	582.303***	4,037.437***	130.891***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3

	Dependent variable (aggregate lignite generation):		
	Simulated output	Actual output	Observed - simulated output
	(1)	(2)	(3)
Hydro	-0.070^{*}	-0.102^{***}	-0.032
	(0.040)	(0.015)	(0.037)
Nuclear	-0.036	-0.013	0.023
	(0.066)	(0.025)	(0.062)
Solar	-0.076^{***}	-0.160^{***}	-0.085^{***}
	(0.023)	(0.009)	(0.022)
Wind	-0.050^{***}	-0.194^{***}	-0.144^{***}
	(0.019)	(0.007)	(0.017)
Demand	0.048^{**}	0.126^{***}	0.078^{***}
	(0.019)	(0.007)	(0.018)
price.euets	-92.963^{***}	-52.870^{***}	40.093
	(33.442)	(12.553)	(31.205)
price.gas	723.714^{***}	138.542^{***}	-585.172^{***}
	(68.274)	(25.627)	(63.708)
price.coal	-65.491^{*}	-32.739^{**}	32.752
	(35.673)	(13.390)	(33.287)
Observations	493	493	493
R^2	0.896	0.978	0.498
Adjusted R^2	0.895	0.978	0.490
Residual Std. Error (df = 485)	6,681.604	2,507.986	6,234.746
F Statistic (df = 8; 485)	524.474^{***}	$2{,}707.222^{***}$	60.230^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix 3

We use the following reactance parameters for transmission lines:

Voltage (kV)	Reactance (Ω/km)
132	0.387
220	0.301
300	0.27
380	0.246
750	0.15

Where reactance is expressed in ohms (Ω) per kilometer. The total reactance of a 220 kV transmission line with a length of 15 km is thus 4.52 Ω, and the corresponding admittance (which we use to construct the PTDF matrix) is its inverse: 0.22 (expressed in siemens, SI).

We use the following parameters for transformers:

Transformer type	S_n (MVA)	U_h (kV)	U_L (kV)	$u_{kr}(\%)$	$u_{Rr}(\%)$
220/110 kV	300	110	220	12	0.128
380/110 kV	350	110	380	22	0.257
380/220 kV	600	110	380	18.5	0.25

Given these parameters, we calculate the impedances of the transformers using the following formula:

$$\sqrt{(\frac{u_{kr} \times U_H^2}{100 \times S_n})^2 - (\frac{u_{Rr} \times U_L^2}{100 \times S_n})^2} \tag{10}$$

Where $S_n$is the rated power flow, U_H and U_L are the higher and lower voltages of the transformer, u_{kr} is the absolute short circuit voltage and u_{Rr} is the real part of short circuit voltage.

All of our technical assumptions are based on Hoersch et al. (2018).

Appendix 4

A key concern that arises in our model is that the heat rates of units are not necessarily static. In particular, the heat rate of a combined cycle unit depends on how the unit is operated. Due to the dependence on multiple cycles, higher thermal efficiencies are obtained when units are operated continuously instead of intermittently. While we do not attempt to factor a variable heat rate into our model in the form of a variable marginal cost, this variation is a possible concern for our estimation of implied emissions. To assess the magnitude of this effect, we analyze the operation of a subset of combined cycle units and their total annual emissions using hourly output data from Entso-E (*ENTSO-E Transparency Platform: Actual Generation per Generation Unit* (2025)) and annual carbon dioxide emissions from the EU-ETS emission registry (*European Union Emissions Trading Registry* (2025)). Our hypothesis is that the ratio of annual emissions to annual electricity output depends on i) the overall capacity utilization of a combined cycle unit and ii) the variance of generation and/or the number of operation starts. A higher overall capacity utilization is expected to imply a lower ratio of carbon dioxide emissions to electricity output, and the variance of generation and/or number of generation starts is expected to imply a higher ratio of carbon dioxide emissions to electricity output.

We define the ratio of carbon dioxide emissions to electricity generated as *marginal emissions*. This is the element $\frac{ef_n}{\eta_n}$ in the formula we use to calculate the total marginal cost. Since the CO2-to-energy content of the natural gas does not vary across time or unit, the differences we observe in the marginal emissions is explained by variation in the heat rate.

We use data on the hourly generation of a selection of combined cycle generation units in Europe. We use unit-level data off the thermal capacities of these generation units from the Pypsa-Eur power plant database to calculate hourly capacity utilization factors. We furthermore use data on the annual emissions of generation units and/or power plants from the EU Emissions Trading System (EU-ETS) database. The EU-ETS database is not always consistent with whether annual emissions are reported on the level of a generation unit or a power plant (one power plant may consist of multiple generation units). To ensure consistency, we aggregate data to the power plant level even when we have emission data on the generation unit level.

We measure the standard deviation of generation by calculating the capacity utilization for all hours by dividing hourly output with the thermal capacity of the unit and rounding the values to the nearest integer (0 or 1). Our measure of standard deviation therefore captures large changes in the operation of the unit; i.e., how often a unit changes from no or low output to high output or output at the thermal capacity of the unit. We measure generation starts by calculating the number of hours per year that the unit goes from zero output to a positive output.

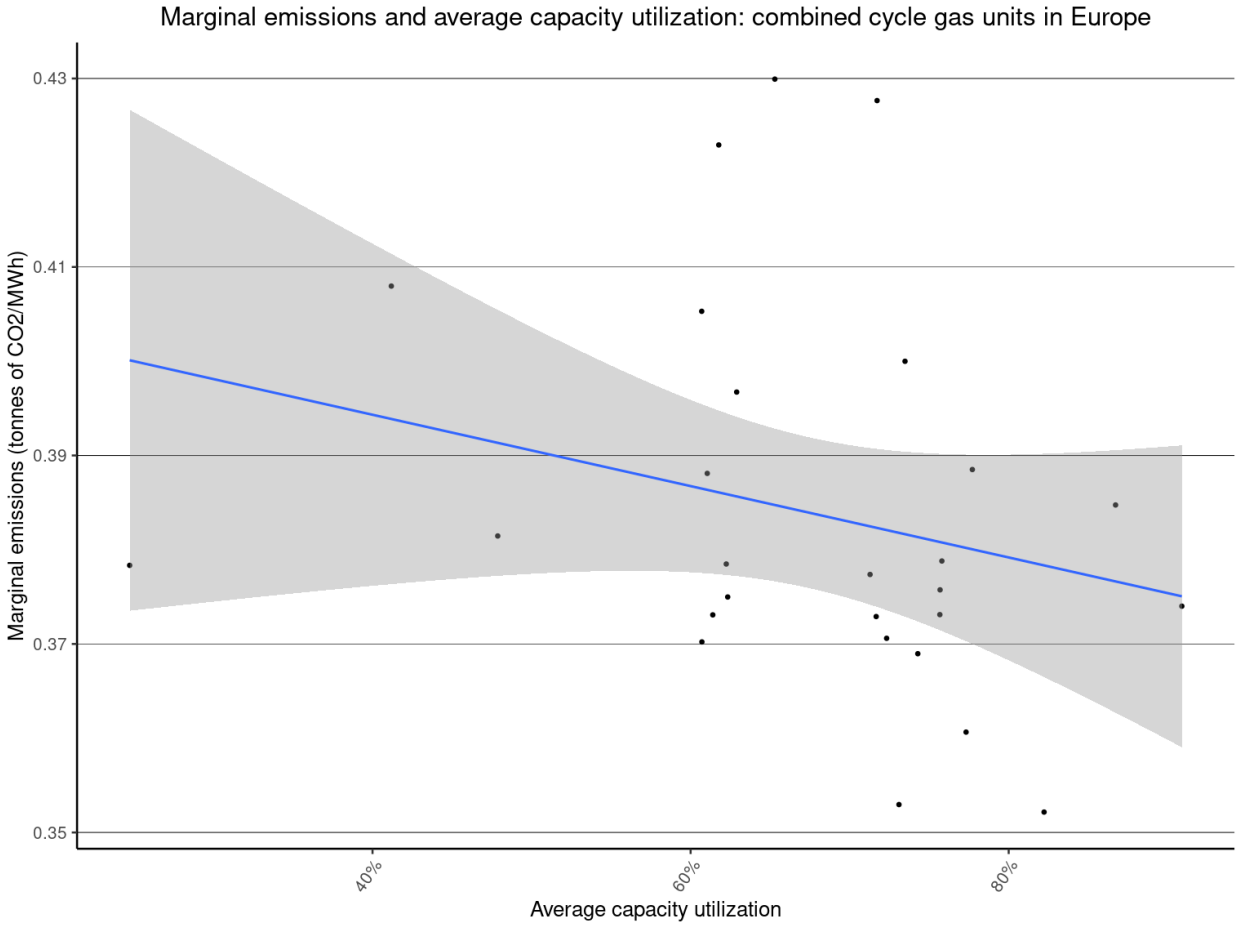


Figure 26: The implied emission factor of selected combined cycle gas units and average capacity utilization: scatterplot

The data on average capacity utilization supports our hypothesis. Units with a higher average capacity utilization have on average lower marginal emissions. A higher sustained capacity utilization is predicted to imply a lower heat rate, i.e., a higher efficiency.

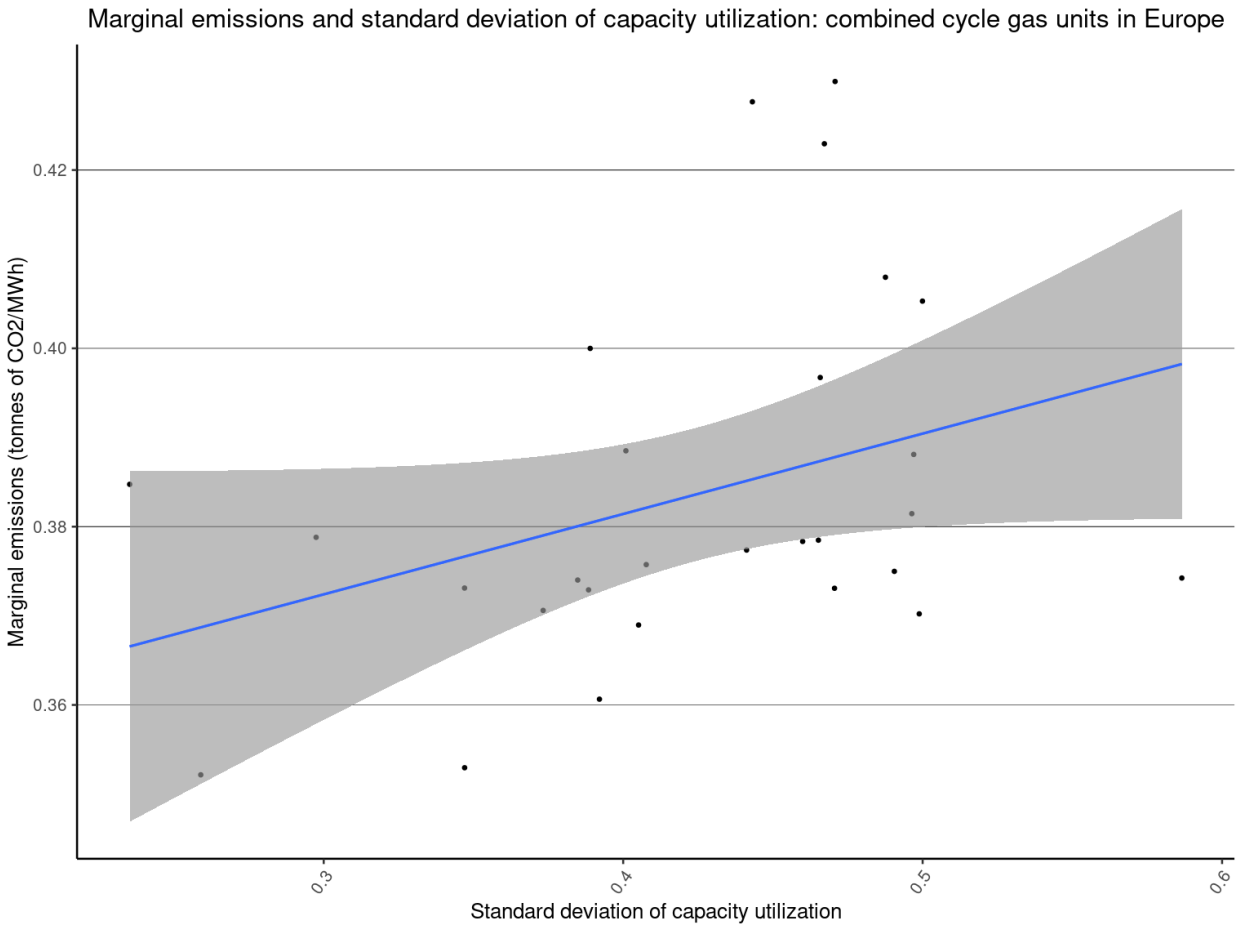


Figure 27: The implied emission factor of selected combined cycle gas units and the standard deviation of capacity utilization: scatterplot

The data on the standard deviation capacity utilization supports our hypothesis. Units with a higher standard deviation of capacity utilization have on average higher marginal emissions. Variance in generation prevents a combined cycle unit from operating in ideal conditions, which in turn leads to a lower thermal efficiency, i.e., a higher heat rate.

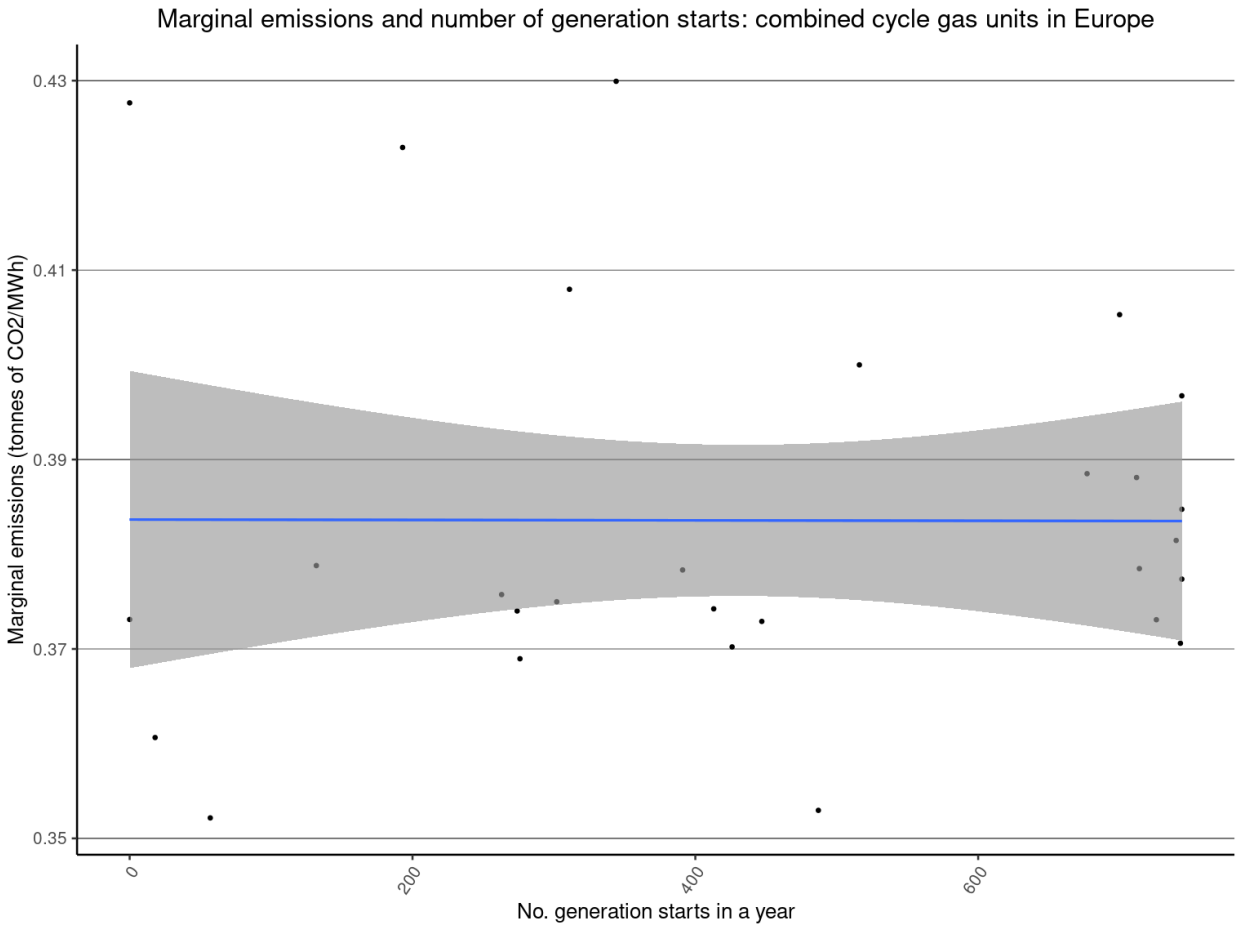


Figure 28: The implied emission factor of selected combined cycle gas units and the number of generation starts: scatterplot

The data on the number of generation starts is inconclusive. There does not seem to be a relationship between the number of generation starts and marginal emissions. This result is perplexing, but it does not necessarily constitute proof against our hypothesis. We define a generation start as an event where the output changes from zero to a positive value, but this implies that the number of starts captures anything from ramping up generation to maximum thermal capacity or ramping generation to a very small level. Some units operate continuously on a low output for sustained periods of time, while some are only active on peak demand hours.

Our marginal emission estimates allow us to pinpoint the heat rate, given an assumption on the emission factor of the fuel. While we prefer to use the expert estimates on heat rates

in our simulation,[17] we can use our marginal emission estimates to verify that the heat rate assumptions we use in our model are accurate. Apart from some outliers that are probably due to mismatching, the majority of our marginal emission estimates fall between 0.35 and 0.5 $TnCO2/MWh$. We assume an emission factor of 50 $TnCO2/TJ$, which is equivalent to 0.18 $TnCO2/MWh$ (by the fact that $1MWh = 0.0036TJ$). It follows that our marginal emission estimates imply thermal efficiencies for combined cycle units that are between 51 % and 35 %, which correspond to implied heat rates between 6690 and 10662.5. These results suggest that the heat rate assumption we use in the simulation for combined cycle units is realistic. As with other units, the heat rates of combined cycle gas units depend on their age, and possible retrofits. While the way in which combined cycle units are operated affects their heat rate, we do not account for this variance in our simulation due to computational limitations.

[17]There are consistency issues in the datasets we use to calculate marginal emissions. In particular, the different naming conventions used in all datasets force us to match data by hand. The EU emission trading registry includes industrial activities as well as power generation, which means that there is a possibility of mismatching. Some entries in the EU ETS registry furthermore correspond to entire power plants, while some entries correspond to single generation units.

Appendix 5

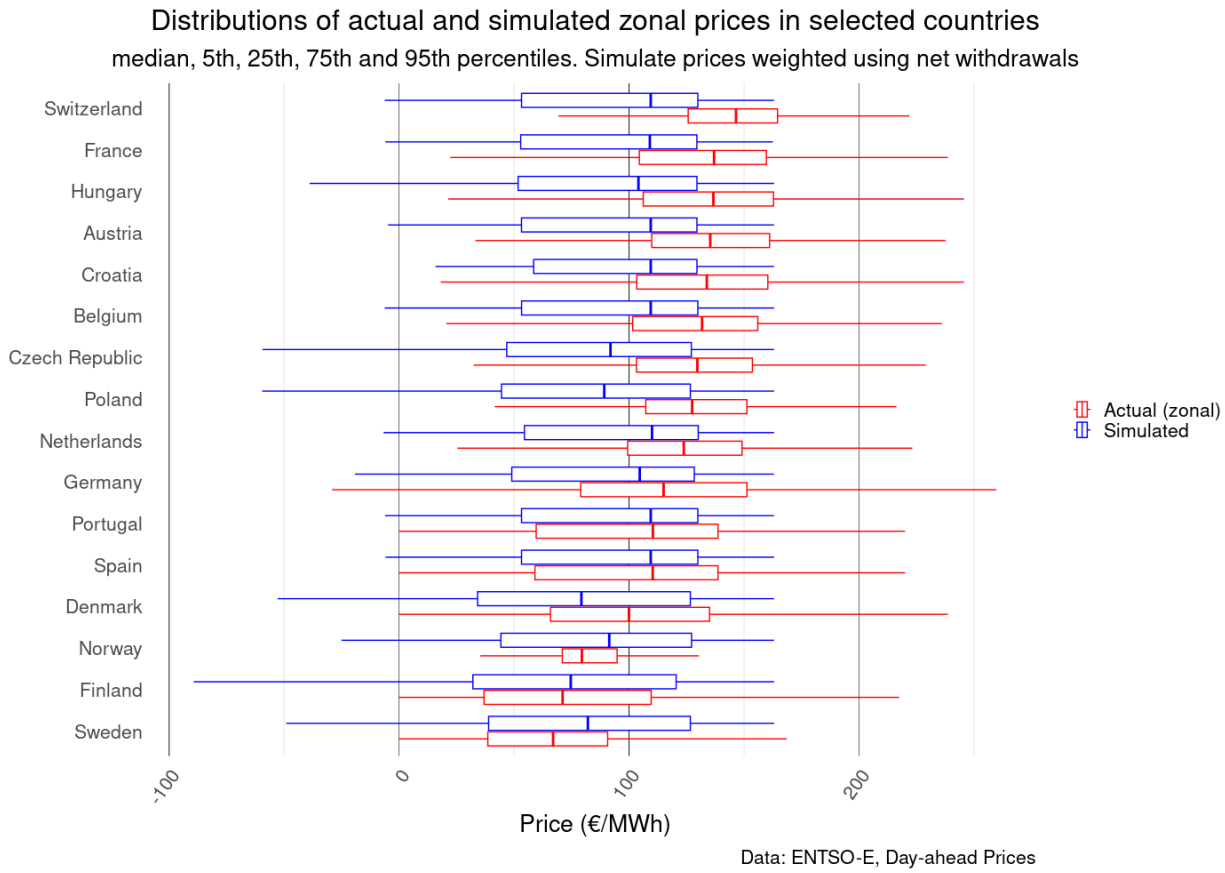


Figure 29: Distribution of country-level average simulated hourly prices (blue) weighted by net withdrawals (nodes with net injections are assigned weight 0) and actual hourly prices from the year 2023 (red). Simulated prices represent the average hourly amount paid by loads for electricity in our simulation. Boxplot distribution ($5\% - 25\% - 50\% - 75\% - 95\%$).

Appendix 6

In this appendix, we present a more detailed analysis of our 6-node transmission system example with two TSOs. We analyze the redispatch process and its associated costs under a number of different assumptions about the redispatch.

The key sources of inefficiency in our model of sequential redispatch are the lack of coordination between the TSOs and the TSOs objective to minimize the redispatch cost at every step. Consider the redispatch process starting from the initial allocation $(750, 0, 750, 100)$ and assume TSO 1 moves first. Given the short-term cost-minimizing objective of the TSOs, TSO1 moves from $(750, 0, 750, 100)$ to $(500, 250, 750, 100)$ (where line flows within TSO 1's control area do not violate physical feasibility constraints), and TSO 2 responds to this by moving to $(576, 174, 323, 527)$, which is a physically feasible dispatch. However, if TSO 1 was not forced to move to a physically feasible dispatch, the process could play out differently. If TSO 1 moves from $(750, 0, 750, 100)$ to $(576, 174, 750, 100)$ (where line flows within TSO 1's control area still violate physical feasibility constraints), TSO 2 responds to this by moving to $(576, 174, 323, 527)$, which is the actual variable cost-minimizing dispatch. We have so far assumed that the TSOs redispatch independently, but this assumption does not preclude the TSOs anticipating their counterpart's actions when choosing their move in the sequential redispatch process. In this simple example, the TSOs can straightforwardly anticipate their counterpart's best-response to their action given that both TSOs have the objective to achieve the dispatch that minimizes total variable costs. In the real world, this logic may not hold. Real-world power systems are much more complex than this example and the European wholesale market includes tens of different TSOs. We cannot assume that each TSO can accurately map its action space and anticipate how other TSOs will respond to their redispatch. The sequential nature of the redispatch process in out simplified model is also an abstraction, and does not necessarily reflect how redispatching occurs in existing zonal markets.

We also recall that the actual cost-minimizing physically feasible dispatch for $D_1 = D_2 = 800$ is $(600, 0, 400, 600)$ (this is the solution to the economic dispatch probler that is yielded by nodal market clearing), which has a total variable cost of $110,000$ €, which is significantly lower than the cost-minimizing physically feasible dispatch given the zonal power balances that result from the initial market-clearing in the zonal market model $(750, 0, 750, 100)$. We thus see that another key source of inefficiency in our simplified model is the fact that TSOs cannot change the zonal power balance by reallocating generation from one control area to another. If the TSOs could coordinate the redispatch process, they could redispatch across pricing zones. It is unclear how this could occur without explicit coordination (compared to the above example of TSOs anticipating each other's best responses). It should be obvious to the reader that a centrally operated redispatch process would increase the efficiency in the redispatch process, but this improvement would likely be meager compared to the costs the

TSOs (or one hypothetical central TSO) would incur from redispatching. The only ways of reducing or elinating these redispatch costs would be to consider all transmission constraints in the initial market clearing (which would imply nodal prices), or change how generation units are compensated for redispatching.

The total variable cost of the dispatch is a meaningful value, but its effects on the operating costs of the power system may not be that straightforward. When $D = 800$, all of the cheap generation capacity is in use in the initial zonal market-clearing dispatch − it follows that the zonal price is set by the expensive generator in both pricing zones, and both the cheap and expensive generators receive the market-clearing price for all energy supplied. However, inframarginal rents obtained by cheap generators give incentives for investing in cheaper generator rather than expensive generator. Lower total variable cost implies that cheap generators are relied more to supply electricity, and thus incentives to invest in cheap generation are likewise larger. Lower total variable costs in this contexts also imply that expensive generation is redispatched-up less. Thus it is a useful measure of efficiency.

TSOs have multiple different sources of revenue. Most importantly, these include network tariffs, revenues from different types of ancilliary service markets, and merchant surpluses. Our model does not include any grid tariffs or ancilliary services markets, so we focus only on merchant surpluses. These surpluses arise from price differences between importing and exporting nodes and zones. In particular, we compare the merchant surpluses that arise in the six-node example under our models of nodal and zonal pricing. We contrast these surpluses to the redispatching costs of operating a zonal market. We analyze these surpluses and costs under a variety of different assumptions about how tariffs are levied from market participants. We set $D = 800$ and report results in the following tables.

Market-clearing assumption	Consumer costs	Generator profits	Total variable costs (final)
1	160,000	104,200	119,350
2	228,700	104,200	119,350
3	274,440	134,200	119,350
4	160,000	100,000	110,000
5	200,000	0	110,000

Market-clearing assumption	Redispatch costs	Merchant surplus	TSO profits
1	68,700	0	-68,700
2	68,700	0	0
3	82,440	0	0
4	50,000	0	-40,000
5	0	96,500	96,500

Market-clearing assumptions (we assume that sequential redispatch always starts from TSO 1):

1. Zonal pricing with sequential non-cooperative redispatch, no load tariffs
2. Zonal pricing with sequential non-cooperative redispatch, redispatch costs levied from loads
3. Zonal pricing with sequential non-cooperative redispatch, redispatch costs levied from generators (20 €/MWh) and loads (the difference between TSO losses and tariffs paid by generators, generators pass grid fees to marginal costs)
4. Zonal pricing with sequential redispatch with perfect coordination (or one central TSO), no load tariffs
5. Nodal pricing, no tariffs

These results summarise and highlight several of the issues we have outlined. Even though zonal pricing with redispatch may appear to lead to lower consumer prices (assumption 1), total variable costs are higher than they would be under nodal pricing, since expensive generators are relied on more than would be necessary. Redispatch results in significant costs to TSOs, which have to be covered somehow so that TSOs do not make losses. Levying redispatch costs in full from loads results in higher effective consumer prices than would be the case under nodal pricing (assumption 2). The other option is to levy grid fees from generators (assumption 3). If generators can pass these costs to their offer prices in full (as we assume), generators end up with higher profits from inframarginal rents and the redispatch process and effective consumer prices end up being higher than they would be if redispatch costs would be fully covered by levying grid fees from loads. Assuming no inefficiencies in the redispatch process allows TSOs to cover redispatch costs by levying grid fees from consumers, who would face on average the same effective prices as they would under nodal pricing (assumption 4). However, nodal pricing would allow the TSOs to make significant profits from merchant surpluses, i.e., the the price differences between the purchasing and selling price of electricity implied by nodal pricing (assumption 5). However, the generators

in our simplified model do not make any profits under nodal pricing (which is an artifact of our assumption that there is only one type of generation units in each node; either cheap of expensive, and by no means a general propert of nodal pricing). The TSOs can use the resulting profits to invest in the power grid and thus increase the capacity of transmission lines, alleviating the need for redispatch. In all of our examples of zonal market clearing, TSOs either make zero or negative profits, which does not leave any resources to invest in the grid. Aggravating this problem is the fact that market-based redispatch will give market participants and investors incentives for behaviour that increases grid congestion in the short and the long runs respectively.

References

Alikhani, P., Brinkel, W., Nico an Schram, Lampropoulos, I., & van Sark, W. (2023). *Marginal emission factors in power systems: The case of the netherlands* (Tech. Rep.).

Aravena, I., & Papavasiliou, A. (2017). Renewable energy integration in zonal markets. *IEEE Transactions on Power Systems*, *32*, 1334–1349.

Biggar, D. R., & Hesamzadeh, M. R. (2014). *The economics of electricity markets*. Wiley.

Bindu, S., Olmos, L., & Chaves-Ávila, J. P. (2024). The devil in the details: The factors determining the selection of intrazonal congestion management methods acros europe. *Heliyon*, *10*.

Bjørndal, M., & Jørnsten, K. (2001). Zonal pricing in a deregulated electricity market. *The Energy Journal*, *22*(1), 51–73.

Bohn, R. E., Caramanis, M. C., & Schweppe, F. C. (1984). Optimal pricing in electrical networks over space and time. *The RAND Journal of Economics*, *15*.

Conversion rates for natural gas (Tech. Rep.). (2025). U.S. Energy Information Administration. (`https://www.eia.gov/tools/faqs/faq.php?id=45&t=8`)

Die deutsche braunkohlenwirtschaft: Historische entwicklungen, ressourcen, technik, wirtschaftliche strukturen und umweltauswirkungen (Tech. Rep.). (2017). Agora Energiewende. (`https://www.agora-energiewende.de/fileadmin/Projekte/2017/Deutsche_Braunkohlenwirtschaft/Agora_Die-deutsche-Braunkohlenwirtschaft_WEB.pdf`)

Ding, F., & Fuller, J. D. (2005). Nodal, uniform, or zonal pricing: distribution of economic surplus. *IEEE Transactions on Power Systems*, *20*.

Eicke, A., & Schittekatte, T. (2022). Fighting the wrong battle? a critical assessment of arguments against nodal electricity prices in the european debate. *Energy Policy*, *170*, 360–376.

Electric power annual 2023 (Tech. Rep.). (2023). U.S. Energy Information Administration. (`https://www.eia.gov/electricity/annual/pdf/epa.pdf`)

Energy in belchatow after lignite: Future-proofing energy generation in belchatow, poland (Tech. Rep.). (2022). Bloomberg NEF. (`https://assets.bbhub.io/professional/sites/24/BNEF-Energy-in-Belchatow-After-Lignite_FINAL_English.pdf`)

Entso-e grid map (Tech. Rep.). (2025). European Network of Transmission System Operators for Electricity. (https://www.entsoe.eu/data/map/)

Entso-e transparency platform: Actual generation per generation unit (Tech. Rep.). (2025). European Network of Transmission System Operators for Electricity. (https://m-transparency.entsoe.eu/generation/r2/actualGenerationPerGenerationUnit/show)

Entso-e transparency platform: Costs of congestion management (Tech. Rep.). (2025). European Network of Transmission System Operators for Electricity. (https://transparency.entsoe.eu/congestion-management/r2/costs/show)

Euphemia public description: Single price coupling algorithm (Tech. Rep.). (2024). All NEMO Committee (Nominated Electricity Market Operators). (https://www.nordpoolgroup.com/globalassets/download-center/single-day-ahead-coupling/euphemia-public-description.pdf)

European union emissions trading registry (Tech. Rep.). (2025). European Union. (https://union-registry-data.ec.europa.eu/report/welcome)

for the Cooperation of Energy Regulators, E. U. A. (2024). *Transmission capacities for cross-zonal trade of electricity and congestion management in the eu (2024 market monitoring report)* (Tech. Rep.). Author.

Germeshausen, R., & Wölfing, N. (2020). How marginal is lignite? two simple approaches to determine price-setting technologies in power markets. *Energy Policy*, *142*.

Graf, C., Quaglia, F., & Wolak, F. A. (2020). *Simplified electricity market models with significant intermittent renewable capacity: Evidence from italy* (Tech. Rep.). National Bureau of Economic Research.

Green, R. (2007). Nodal pricing of electricity: How much does it cost to get it wrong? *Journal of Regulatory Economics*, *31*, 125–149.

Grimm, V., Martin, A., Sölch, C., Weibelzahl, M., & Zöttl, G. (2022). Market-based redispatch may result in inefficient dispatch. *The Energy Journal*, *43*(5), 205-230.

Harvey, S. M., & Hogan, W. W. (2000). *Nodal and zonal congestion management and the exercise of market power* (Tech. Rep.). Harvard University.

Hirth, L., & Schlecht, I. (2020). *Market-based redispatch in zonal electricity markets: The preconditions for and consequence of inc-dec gaming* (Tech. Rep.). Leibniz Information Centre for Economics, Kiel, Hamburg.

Hoersch, J., Hofmann, F., Schlachtberger, D., & Brown, T. (2018). Pypsa-eur: An open optimisation model of the european transmission system. *Energy Strategy Reviews*, *22*, 207–215. doi: 10.1016/j.esr.2018.08.012

Ipcc guidelines for national greenhouse gas inventories (Tech. Rep.). (2006). Intergovernmental Panel on Climate Change.

Karhinen, S., & Huuki, H. (2020). How are the long distances between renewable energy sources and load centres reflected in locational marginal prices? *Energy*, *210*.

Kristiansen, T. (2020). The flow based market coupling arrangement in europe: Implications for traders. *Energy Strategy Reviews*, *27*.

Leuthold, F., Rumiantseva, I., Weigt, H., Jeske, T., & von Hirschhausen, C. (2007). *Nodal pricing in the german electricity sector - a welfare economics analysis, with particular reference to implementing offshore wind capacities* (Tech. Rep.). Working Paper.

Modern german lignite plant margins halve from 2024 (Tech. Rep.). (2024). Argus Media. (`https://www.argusmedia.com/en/news-and-insights/latest-market-news/2195015-modern-german-lignite-plant-margins-halve-from-2024`)

Natural gas citygate price in california (Tech. Rep.). (2025). U.S. Energy Information Administration. (`https://www.eia.gov/dnav/ng/hist/n3050ca3m.htm`)

Neuhoff, K., & Hobbs, B. (2013). Renewable electric energy integration: Quantifying the value of design of markets for international transmission capacity. *Energy Economics*, *40*, 760–772.

New coal-fired power plant performance and cost estimates (Tech. Rep.). (2009). Sargent & Lundy LLC. (`https://www.epa.gov/sites/default/files/2015-08/documents/coalperform.pdf`)

Production of lignite in the eu - statistics (Tech. Rep.). (2025). Eurostat. (`https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Production_of_lignite_in_the_EU_-_statistics`)

Report on the locational marginal pricing study of the bidding zone review process (Tech. Rep.). (2022). European Network of Transmission System Operators (ENTSO-E). (`https://www.nordpoolgroup.com/globalassets/download-center/single-day-ahead-coupling/euphemia-public-description.pdf`)

Ronellenfitsch, H., Timme, M., & Witthaut, D. (2014). A dual method for computing power transfer distribution factors. *IEEE Transactions on Power Systems*, *32*, 1007–1015.

Roth, A. E. (2007). The art of designing markets. *Harvard business review*, *85*(10), 118.

Schram, W., Lampropoulos, I., AlSkaif, T., , & van Sark, W. (2019). *On the use of average versus marginal emission factors* (Tech. Rep.). Copernicus Institute of Sustainable Development, Utrecht University.

Schönheit, D., Kenis, M., Lorenz, L., Möst, D., Delarue, E., & Bruninx, K. (2021). Toward a fundamental understanding of flow-based market coupling for cross-border electricity trading. *Advances in Applied Energy*, *2*.

Seifi, H., & Sepasian, M. S. (2011). *Electric power system planning.* Springer.

Stoft, S. (1997). Transmission pricing zones: simple or complex? *The Electricity Journal*, *10*(1), 24-31.

Triolo, R. C., & Wolak, F. A. (2022). Quantifying the benefits of a nodal market design in the texas electricity market. *Energy Economics*, *112*.

Understanding lignite generation costs in europe (Tech. Rep.). (2014). Booz Co. (`https://www.ppcgroup.com/media/qbmj0twz/understanding-lignite-generation-costs-in-europe.pdf`)

Us energy information administration: Carbon dioxide emissions coefficients (Tech. Rep.). (2025). US Energy Information Administration. (`https://www.eia.gov/environment/emissions/co2_vol_mass.php`)

Van den Bergh, K., Boury, J., & Delarue, E. (2016). The flow-based market coupling in central western europe: Concepts and definitions. *The Electricity Journal*, *29*.

Walton, S., & Tabors, R. D. (1996). Zonal transmission pricing: methodology and preliminary results from the wscc. *The Electricity Journal*, *9*(9), 34-41.

Weber, L., Gilles, L., & Moser, A. (2022). Influence of an inter-tso cooperation on the redispatch demand in europe. In *2022 18th international conference on the european energy market (eem)* (p. 1-6). doi: 10.1109/EEM54602.2022.9921006

Wolak, F. A. (2011). Measuring the benefits of greater spatial granularity in short-term pricing in wholesale electricity markets. *American Economic Review*, *101*.

Wolak, F. A. (2015). Measuring the competitiveness benefits of a transmission investment policy: The case of the alberta electricity market. *Energy Policy*, *85*, 426–444.

Wolak, F. A. (2021). Wholesale electricity market design. In *Handbook on electricity markets* (pp. 73–110). Edward Elgar.

Zahler, J., Weiss, A. M., & Wendlinger, E. (2023). *Congestion management: Redispatch 2.0 in international comparison* (Tech. Rep.). Forschungsstelle für Energiewirtschaft. (https://www.ffe.de/en/publications/congestion-management-redispatch-2-0-in-international-comparison/)

Zarnikau, J., Woo, C. K., & Baldick, R. (2014). Did the introduction of a nodal market structure impact wholesale electricity prices in the texas (ercot) market? *Journal of Regulatory Economics*, *45*, 194–208.