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Keywords Electricity, investment, structural uncertainty, market design, bidding zones, nodal pricing.

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The role of expectations for market design – on structural regulatory uncertainty in electricity markets

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Abstract. Ongoing policy discussions on the reconfiguration of bidding zones in European electricity markets induce structural uncertainty about the future market design. This paper deals with the question of how this structural uncertainty affects market participants and their long-run investment decisions in generation and transmission capacity. We propose a stochastic multilevel model, which incorporates generation capacity investment, network expansion and redispatch, taking into account uncertainty about the future market design. Using a stylized two-node network, we disentangle different effects that uncertainty has on market outcomes. Our results reveal that expectations about future market structures have an important effect on investment decisions. Unlike most parametric uncertainties, structural uncertainty about the future market design can have a positive effect on welfare, even if a market design change does not actually take place, although there are distributional effects. This also implies that the welfare gains of a change to a more efficient market design are lower if market participants already anticipate this change.

1. Introduction

The need for decarbonization of the electricity system, together with structural changes in electricity demand and generation costs, is driving significant investment in new and upgraded electricity transmission and generation capacity. Transmission and generation investment projects have long lead times and lifespans, and are therefore subject to significant levels of risk and uncertainty about among others, future costs, demand levels and patterns, and regulation.

In response, planning methods have evolved to explicitly consider how optimal investment decisions should be made under uncertainty. These include stochastic optimization models, which seek to identify decisions that are optimal given the full range of possible future market conditions (for an overview, see Conejo et al. 2010 and Möst and Keles 2010), and robust optimization models, which optimize decisions such that the worst possible outcomes are still feasible (Ruiz and Conejo 2015). These methods have been applied to a wide range of markets and uncertainties, and the results of these applications clearly show that uncertainty is a key driver of transmission and generation investment (van der Weijde and Hobbs 2012; Muñoz et al. 2017).

However, the uncertainties that are considered in existing studies are all parametric as they affect investment or operational costs, or constrain decision variables.

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Parametric uncertainties are easily included in stochastic or robust models using scenario sets or distributions. However, many sources of uncertainty are not parametric, but structural and therefore much more difficult to model. This is particularly true for regulatory uncertainties, including uncertainty about pricing methods, competition policy, the future existence of markets for ancillary services, and many others. These structural regulatory uncertainties are particularly important, as they are highly idiosyncratic and therefore impossible to hedge perfectly (Ehrenmann and Smeers 2011). Moreover, regulatory uncertainty is never resolved, as in most legal systems policy makers cannot be bound by the decisions of their predecessors. Despite all this, structural regulatory uncertainties have received little attention and few methods are available to model and quantify them. This paper is a first attempt to do so in electricity markets.

One of the sources of structural regulatory uncertainty in electricity markets, particularly in Europe, is the future of zonal market designs. Liberalized electricity markets in Europe currently often operate within national bidding zones. Under this zonal pricing market design, there is a single electricity price in each country, with pre-determined trade capacities implicitly or explicitly auctioned to allow cross-border trade while controlling between-country congestion. Transmission constraints within countries are not accounted for within the market, but are resolved by system operators after market outcomes are announced, usually through cost-based balancing mechanisms or countertrading in balancing markets.

In the short-term, this means that traded quantities might not always be technically feasible in the existing transmission network. The resulting network congestion has to be resolved by the transmission system operator (TSO) via redispatch, i.e., by instructing some generators to increase or decrease their production. This is costly, and depending on redispatch mechanisms may incentivize non-competitive behavior. In the long term, the lack of locational investment signals within zones might result in inefficient investment in power plants, additional transmission investment, and higher redispatch costs. With a growing share of renewables in electricity markets worldwide, network congestion and thus costs for congestion management are increasing in most markets.

Most large US markets have already adopted nodal (or: locational marginal) pricing mechanisms. In these markets, market operators solve large optimization models that calculate the least-cost set of dispatch decisions for all generators on the system, considering at least a linearized representation of all transmission constraints. A price is then calculated for each bus, which reflects the marginal cost of electricity in that specific location. This reduces the need for redispatch, as all constraints have already been included in the market, and gives more efficient investment signals (Holmberg and Lazarczyk 2015).

In Europe, the discussion about a reconfiguration of current bidding zones is ongoing, both in regulatory and academic spheres (e.g., Grimm et al. 2019; Ambrosius et al. 2018; ENTSO-E 2018; Bertsch et al. 2017; Egerer et al. 2016; Grimm et al. 2016b; Plancke et al. 2016; Trepper et al. 2015; CMA 2015; Frontier Economics and Consentec 2011). This debate, though necessary, is a key source of structural regulatory uncertainty. The effects of this uncertainty have not been studied. Many recent studies have attempted to estimate the benefits of adopting nodal pricing and other structural market design changes in European electricity markets (van der Weijde and Hobbs 2011; Neuhoff et al. 2013). However, these usually assume that market design changes happen overnight. In reality, as the European zonal pricing debate shows, market design changes are usually preceded by long periods of uncertainty, during which different options are suggested and debated, and during which it is unclear which, or even whether, changes will come about. There is, therefore, a need to understand how these types of structural regulatory uncertainty affect investment and market operation.

This paper is a first attempt to address this issue of structural regulatory uncertainty in electricity markets. We specifically consider the structural uncertainty caused by the European zonal pricing debate, but our methods and qualitative conclusions carry over to other types of regulatory uncertainty. We consider a situation in which a transmission planner invests in transmission capacity, anticipating a second stage in which generation investment takes place, followed by market operation and cost-based redispatch. At the investment stage, market participants do not know whether the market will consist of one or multiple bidding zones; instead, they assign a probability to each scenario. We first analyze this bidding zone uncertainty in a small two-bus model, to qualitatively explore the results and their main drivers.

We show that uncertainty about market design is fundamentally different from uncertainty in market parameters, e.g., generation costs. Whereas most previous studies have shown that the latter has negative implications, leading to a decrease in social surplus, market design uncertainty can have a positive effect. Indeed, even if market participants believe that there is a small possibility that additional bidding zones will be implemented, this can already have a major impact on investment decisions, even if this actual change never takes place. Hence, it is at least as important to understand market participants' expectations about future market designs as it is to determine what markets might actually look like. However, there are important distributional effects, between producers and consumers and between market participants located at different zones, which need to be taken into account.

The next two sections introduce the methodology. Section 4 describes a two-node example and Section 5 provides results including regulatory uncertainty. Section 6 discusses the main results and Section 7 concludes.

2. Modeling investment incentives under regulatory uncertainty

In this section, we introduce the underlying setting for our stochastic trilevel market model accounting for regulatory uncertainties. The setting follows the multilevel approach of Grimm et al. (2016a), where the regulator decides on network capacity, while firms decide on investment in generation capacity and production in a competitive market environment.

2.1. **Timeline.**

To be able to capture this situation in a feasible model, we consider a sequence of long-term and short-term decisions. The timing of a suitable stylized game is illustrated in Figure 1. First, the TSO decides on welfare maximizing transmission capacity expansion in anticipation of the subsequent decisions taken by private firms and its own redispatch quantities. Additionally, the TSO can invest in backup capacity to balance infeasible spot market solutions, anticipating the actual need of backup capacity after spot market trading in each operating point. This is followed by generation capacity investment of private generation companies. They take this decision under a profit maximization objective and in anticipation of marginal revenues earned during spot market trading over the lifetime of the respective unit. Investments in transmission and generation capacity are long-term decisions, which are only taken once, and have to be taken for several years in advance. The TSO and private firms cannot be sure what the market design will look like by the time of commissioning. All long-term decisions are therefore taken under uncertainty about the future market design. In our specific case, there exists uncertainty about the exact number of bidding zones. However, the TSO and private investors assign probabilities to all possible events. These probabilities are subjective and are not related to the actual probability of a change in market design, which is fundamentally unpredictable. They maximize the expected values of welfare and profits, respectively. After all market participants have taken long-term decisions under uncertainty, one of the possible market design scenarios is realized, i.e., the number of bidding zones is known to all market participants. Now, electricity is traded in multiple periods at the spot markets, whereby intra-zonal network capacity is neglected, while inter-zonal network capacity is taken into account. In case market results are not feasible in the physical network, the TSO carries out cost-based redispatch. This means that the TSO can call power plants in the import-constrained regions to increase production, and instruct plants in the export-constrained regions to reduce production. In case traded quantities are still infeasible even after cost-based redispatch, the TSO can furthermore make use of backup capacity and increase production in import-constrained areas.

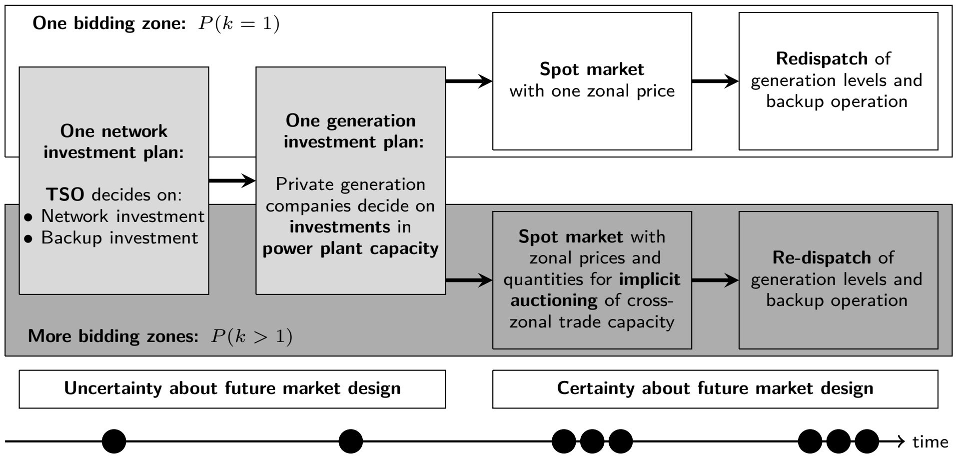


FIGURE 1. Timing of decisions on zonal configuration under uncertainty

2.2. **Translation to a trilevel model.** In the following we sketch how this setting can be translated into a stochastic trilevel model.

Level 1. At the first level, the TSO decides on transmission capacity expansion as well as investment in backup capacity under uncertainty about the future market design as to maximize expected welfare, anticipating all subsequent levels. The amount of backup capacity is determined so that feasibility is achieved in each scenario, i.e., the TSO builds the maximum capacity that is needed across all scenarios.

Level 2. At the second level, generation capacity investment and spot market trading in multiple periods by private firms is modeled. These decisions can be considered jointly at one level due to (i) the assumption of perfect competition and (ii) the absence of time interdependencies such as load-changing costs or storage constraints. Hence, there are no interdependencies between the different subsequent periods of spot market trading. We can therefore solve all periods of spot market trading jointly at level 2, before determining cost-based redispatch at level 3.

Level 3. At the third level, cost-based redispatch takes place, which is determined by the TSO. Again, cost-minimizing redispatch problems of all periods are determined jointly at the third level due to the absence of intertemporal dependencies.

Model interdependencies. As the TSO anticipates all subsequent levels, spot market behavior by private firms and redispatch decisions are part of the TSO's optimization problem. The first level therefore depends on the decisions of the second and third level, whereas the second level only depends on the line investment decisions taken at the first level. Note that due to the assumption of cost-based redispatch, third-level decisions of the TSO do not affect the profits of private firms and thus their investment and production decisions at the second level. Investment in backup capacity also does not affect spot market outcomes, as backup capacity is only ramped up by the TSO in case redispatch of private generation capacity is not sufficient to alleviate network congestion. The third level depends on decisions from the first and second level. The dependencies of the trilevel model are illustrated in Figure 2.

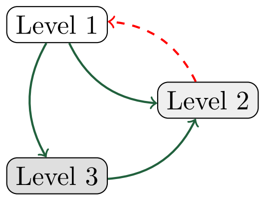


FIGURE 2. Dependencies of the three-level model: Green, solid arcs denote dependencies on continuous variables, the red, dashed arc denotes dependencies on discrete variables. Source: Grimm et al. (2019).

Grimm et al. (2016a) show that the deterministic trilevel market model can be reformulated as a bilevel model, aggregating the first level (transmission capacity expansion and backup capacity) and the third level (redispatch), exploiting the weak coupling of the three levels as described previously. We explain how this reformulation can be applied to the stochastic model in Section 3.6.

3. The trilevel market model

In this section, we will explain in detail how we model the interaction of the market participants as described above. We will first explain how uncertainty about the future market design is implemented, continue with the basic technical model setup and a detailed description of each level, before concluding the chapter with a discussion on the solution approach.

3.1. **Modeling uncertainty.** To account for regulatory uncertainty within the decision process, we make use of a stochastic optimization approach as described in Birge and Louveaux (2011). This means that we consider a set of decisions that have to be taken without full information on a random event. After realization of the uncertain event, full information about the random event is received and the remaining variables are decided upon. These variables can be determined optimally for each realization of the uncertain event. In the literature, uncertainty is usually integrated in the form of an uncertain realization of parameters such as costs, demand or production quantities (van der Weijde and Hobbs 2012; Baringo and Conejo 2013; Ehrenmann and Smeers 2011). In our case, however, uncertainty refers to different realizations of market designs, i.e., the spot market is divided into an uncertain number of bidding zones. To model this structural uncertainty about the market design, we introduce the discrete scenario set S, which includes a finite number of possible market design scenarios s. More specifically, each scenario represents a certain zonal configuration with a given number and location of zones.

Each of these scenarios $\mathrm{s} \in \mathrm{S}$ occurs with a probability $\pi_{\mathrm{s}} \in [0,1]$. Short-term variables such as spot market trading and redispatch are determined optimally for each scenario $\mathrm{s} \in \mathrm{S}$ after the regulator has decided on the zonal configuration of the market. Long-term variables, such as investment decisions in transmission and generation capacity, in contrast, have to be made under uncertainty by taking into account the expected value of the random events. All restrictions including uncertain parameters have to be feasible for all scenarios $\mathrm{s} \in \mathrm{S}$, i.e., the solution is then robust with respect to feasibility.

3.2. **Basic economic and technical setup.** In this section, we introduce the basic setup for our model. We consider an electricity transmission network $\mathcal{G}$, consisting of nodes N and transmission lines $L \subseteq N \times N$. The set of lines L is furthermore divided into existing lines L^{ex} and candidate lines L^{new}. The decision about investment in candidate transmission line $l \in L^{\mathrm{new}}$ is taken by the TSO and denoted by $z_l \in \{0,1\}$. We assume that transmission investment is a naturally discrete decision. Line investment cost are denoted by $c_l^{\mathrm{inv}} > 0$. We further account for different bidding zones $Z_{\mathrm{s}} := \{Z_1, \ldots, Z_{|Z_{\mathrm{s}}|}\}$, which form a partition of the node set $N = Z_1 \cup \ldots \cup Z_{|Z_{\mathrm{s}}|}$, where number and configuration of bidding zones depend on scenario $\mathrm{s} \in \mathrm{S}$. Lines that connect nodes of different zones are called inter-zonal lines and denoted by $L_{\mathrm{s}}^{\mathrm{inter}}$. Note that the set of inter-zonal lines depends on scenario $\mathrm{s} \in \mathrm{S}$, as a line can be an inter-zonal line for some zonal configurations, while it is not for others. The specific capacity of each line is denoted by $\bar{f}_l$ and their susceptance by B_l. We further denote sets of in- and outgoing lines by $\delta_{N'}^{\mathrm{in}}$ and $\delta_{N'}^{\mathrm{out}}$, respectively. The time horizon is discretized to a set of equidistant operating points $t \in T$, with $T = \{1, \ldots, |T|\}$ and time steps $\tau = t_{i+1} - t_i$ for all $i = 1, \ldots, |T| - 1$. Flows through line l in operation point $t \in T$ and scenario $\mathrm{s} \in \mathrm{S}$ are denoted by $f_{t,l,\mathrm{s}}$. We model real power flows via a lossless direct current (DC) approximation (Schweppe et al. 1988). Demand at each node $n \in N$ is denoted by $d_{t,n}$ and modeled as a continuous, strictly decreasing and linear demand function $p_{t,n,\mathrm{s}} = p_{t,n,\mathrm{s}}(d_{t,n,\mathrm{s}})$. As a result, the gross consumer surplus is a strictly concave quadratic function:

$$\int_0^{d_{t,n,\mathrm{s}}} p_{t,n,\mathrm{s}}(\xi)\,\mathrm{d}\xi.$$

Note that prices and demand are dependent of the zonal configuration, and thus indirectly depend on the realization of the random bidding zone configuration. At each node $n \in N$, we introduce a finite set of generators G_n^{all}. For simplicity, all generators of the same technology that are located at the same node are aggregated. Firms can invest in generators $g \in G_n^{\mathrm{priv}} \subseteq G_n^{\mathrm{all}}$ with capacity $\bar{y}_g$ at investment cost $c_g^{\mathrm{inv}} > 0$. Additionally, the TSO can invest in backup generators $g \in G_n^{\mathrm{bu}} \subseteq G_n^{\mathrm{all}}$, which can be used in case generation redispatch of private firms does not suffice to alleviate network congestion. In summary, $G_n^{\mathrm{all}} = G_n^{\mathrm{priv}} \cup G_n^{\mathrm{bu}}$. Furthermore, all generators have variable cost $c_g^{\mathrm{var}} > 0$. For every generator $g \in G_n^{\mathrm{priv}}, n \in N$, generated quantities are denoted by $y_{t,g,\mathrm{s}}$ and depend on the zonal configuration $\mathrm{s} \in \mathrm{S}$. The availability factor $\alpha_g \in [0,1]$ denotes power generation per unit of capacity. We denote production quantities that belong to the spot market and redispatch level by the super-index "spot" and "redi", respectively.

Note that investments are taken for a certain time frame T and thus investment costs have to be scaled to fit the respective timeline.

3.3. **First-level problem: transmission line expansion and investment in backup capacity.** At the first level, the regulator decides about optimal transmission capacity investment and investment in backup capacity as to maximize welfare. Welfare is given by the difference of gross consumer surplus and total system costs, i.e., variable costs of production and investment costs for generation capacity and transmission line expansion. The decisions about transmission line expansion and generation capacity investment have to be taken under uncertainty before one of the possible market design scenarios occurs. As an alternative market design influences the outcomes of spot market trading and thus welfare levels, the TSO takes into account the expected value of the latter to account for uncertainty. We obtain the following first-level objective:

$$\begin{aligned}\psi_1 := \sum_{\mathrm{s}\in\mathrm{S}} \pi_{\mathrm{s}} \sum_{n\in N} \sum_{t\in T} \tau \left(\int_0^{d_{t,n,\mathrm{s}}} p_{t,n,\mathrm{s}}(\xi)\,\mathrm{d}\xi - \sum_{g\in G_n^{\mathrm{all}}} c_g^{\mathrm{var}} y_{t,g,\mathrm{s}}^{\mathrm{redi}} \right) \\ - \sum_{l\in L^{\mathrm{new}}} c_l^{\mathrm{inv}} z_l - \sum_{n\in N} \sum_{g\in G_n^{\mathrm{all}}} c_g^{\mathrm{inv}} \bar{y}_g.\end{aligned}$$

The first-level problem thus reads

$$\begin{aligned}\max_{z_l,\bar{y}_g, g\in G_n^{\mathrm{bu}}} \quad & \psi_1 \\ \text{s.t.} \quad & z_l \in \{0,1\} \quad \text{for all } l \in L^{\mathrm{new}}.\end{aligned}$$

3.4. **Second-level problem: generation investment and spot market trading.** At the second level, we model investment in generation capacity and spot market trading by private firms. These decisions are taken to maximize individual profits. We assume perfectly competitive markets, i.e., all companies are price takers. This is a common assumption in electricity market modeling (Boucher and Smeers 2001; Daxhelet and Smeers 2007; Grimm et al. 2016a). In the absence of strategic behavior, profit maximization of each firm yields a welfare-maximizing outcome (Grimm et al. 2019). We can thus consider the outcome-equivalent welfare maximization problem. Decisions about investment in generation capacity are taken under uncertainty, taking into consideration the expected value of spot market outcomes. The investment decision is based on the expected spot market outcomes, where the different market designs enter the objective function with their respective probabilities. The second-level objective thus reads:

$$\psi_2 := \sum_{\mathrm{s}\in\mathrm{S}} \pi_{\mathrm{s}} \sum_{n\in N} \sum_{t\in T} \tau \left(\int_0^{d_{t,n,\mathrm{s}}} p_{t,n,\mathrm{s}}(\xi)\,\mathrm{d}\xi - \sum_{g\in G_n^{\mathrm{priv}}} c_g^{\mathrm{var}} y_{t,g,\mathrm{s}}^{\mathrm{spot}} \right) - \sum_{n\in N} \sum_{g\in G_n^{\mathrm{priv}}} c_g^{\mathrm{inv}} \bar{y}_g.$$

The production $y_{t,g,\mathrm{s}}^{\mathrm{spot}}$ of each generator $g \in G$ is restricted by its capacity limit $\bar{y}_g$ and it is possible to restrict investment in generation capacity up to a maximum capacity $\bar{y}_g^{\mathrm{ub}}$:

$$y_{t,g,\mathrm{s}}^{\mathrm{spot}} \le \alpha_g \bar{y}_g \quad \text{for all } n \in N, g \in G_n^{\mathrm{priv}}, t \in T, \mathrm{s} \in \mathrm{S} \tag{1}$$

$$\bar{y}_g \le \bar{y}_g^{\mathrm{ub}} \quad \text{for all } n \in N, g \in G_n^{\mathrm{priv}}, t \in T, \mathrm{s} \in \mathrm{S}. \tag{2}$$

When deciding about investment in generation capacity and production quantities during spot market trading, firms only receive regional price signals in case inter-zonal lines are congested. Intra-zonal lines are neglected during spot market trading. As a result, in a market setup where all nodes form a single bidding zone, no transmission capacities are considered and thus firms do not receive any regional price signals. However, in a scenario where the market is split into two or more bidding zones, firms can receive zonal price signals in case of constraints on the inter-zonal trade capacity. We account for this structural uncertainty by implementing a zonal version of Kirchhoff's first law, where the number and configuration of inter-zonal lines depend on the respective market design scenario:

$$\sum_{n \in N \cap Z_k} d_{t,n,\mathrm{s}} = \sum_{n \in N \cap Z_k} \sum_{g \in G_n^{\mathrm{priv}}} y_{t,g,\mathrm{s}}^{\mathrm{spot}} + \sum_{l \in \delta_{Z_k}^{\mathrm{in}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{spot}} - \sum_{l \in \delta_{Z_k}^{\mathrm{out}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{spot}} \tag{3}$$

for all $Z_k \in Z_{\mathrm{s}}, t \in T, \mathrm{s} \in \mathrm{S}$. Equation (3) coincides with standard market clearing in case there is only one zone. In case of several zones where at least one zone contains more than one node, equation (3) requires market clearing in each zone. This formulation allows for our structural market design uncertainty to be incorporated.

Flows on inter-zonal lines are restricted by the trade capacity, which is the thermal capacity of each line, scaled with a security factor $\beta_l \in [0, 1]$:

$$-\beta_l \bar{f}_l \le f_{t,l,\mathrm{s}}^{\mathrm{spot}} \le \beta_l \bar{f}_l \quad \text{for all } l \in L_{\mathrm{s}}^{\mathrm{inter}} \cap L^{\mathrm{ex}}, t \in T, \mathrm{s} \in \mathrm{S} \tag{4}$$

$$-z_l \beta_l \bar{f}_l \le f_{t,l,\mathrm{s}}^{\mathrm{spot}} \le z_l \beta_l \bar{f}_l \quad \text{for all } l \in L_{\mathrm{s}}^{\mathrm{inter}} \cap L^{\mathrm{new}}, t \in T, \mathrm{s} \in \mathrm{S}. \tag{5}$$

Note that Kirchhoff's second law is not considered at the spot market level.

Finally, we impose variable bounds on demand and production quantities:

$$y_{t,g,\mathrm{s}}^{\mathrm{spot}} \ge 0 \quad \text{for all } n \in N, g \in G_n^{\mathrm{priv}}, t \in T, \mathrm{s} \in \mathrm{S} \tag{6}$$

$$d_{t,n,\mathrm{s}} \ge 0 \quad \text{for all } n \in N, t \in T, \mathrm{s} \in \mathrm{S}. \tag{7}$$

To summarize, at level two we consider the welfare maximizing generation investment decisions under uncertainty and deterministic, scenario-dependent supply decisions, where supply is constrained by generation capacities and inter-zonal transmission capacities. We thus obtain the following second-level problem:

$$\max_{y_{t,g,\mathrm{s}}^{\mathrm{spot}}, d_{t,n,\mathrm{s}}, \bar{y}_g} \quad \psi_2 \quad \text{s.t.} \quad (3), (4)\text{–}(7).$$

We end up with a concave-quadratic maximization problem with linear constraints. All discrete variables that appear at the second level are decided upon in the first level.

Note that it is also possible to consider a nodal design as a possible scenario. Then, Kirchhoff's first and second law would need to be accounted for in level 2.

3.5. **Third-level problem: cost-optimal redispatch.** At the third level, cost-based redispatch is carried out at minimum costs, i.e., the TSO reallocates spot market supply to ensure feasibility with respect to transmission constraints. This is done for each scenario, after the market design has been decided upon. Only in case reallocation of spot market supply does not suffice to resolve infeasibilities, the TSO has the possibility to ramp up backup generation capacity to ensure feasibility. Total redispatch costs are given by

$$\psi_{3,\mathrm{s}} := \sum_{n \in N} \sum_{t \in T} \tau \sum_{g \in G_n^{\mathrm{all}}} c_g^{\mathrm{var}} \left(y_{t,g,\mathrm{s}}^{\mathrm{redi}} - y_{t,g,\mathrm{s}}^{\mathrm{spot}} \right).$$

During redispatch, generation volumes can be altered by the TSO. These are short-run decisions and thus depend on the respective market design scenario $\mathrm{s} \in \mathrm{S}$.

Trade flows need to account for Kirchhoff's first law, ensuring power balance at each node:

$$d_{t,n,\mathrm{s}} = \sum_{g \in G_n^{\mathrm{priv}}} y_{t,g,\mathrm{s}}^{\mathrm{redi}} + \sum_{l \in \delta_n^{\mathrm{in}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{redi}} - \sum_{l \in \delta_n^{\mathrm{out}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{redi}} \tag{8}$$

for all $n \in N, t \in T, \mathrm{s} \in \mathrm{S}$.

Besides Kirchhoff's first law as given in equation (8), redispatch also has to account for Kirchhoff's second law, which determines the distribution of residual load at one node across its adjacent transmission lines. This is modeled according to the linear DC-lossless approach developed by Schweppe et al. (1988), which determines voltage angles $\theta_{t,n,\mathrm{s}}, t \in T, n \in N, \mathrm{s} \in \mathrm{S}$:

$$f^{\mathrm{redi}}_{t,l,\mathrm{s}} - B_l(\theta_{t,n,\mathrm{s}} - \theta_{t,j,\mathrm{s}}) = 0 \quad \text{for all } l = (n,j) \in L^{\mathrm{ex}}, t \in T, \mathrm{s} \in \mathrm{S} \tag{9}$$

$$- M_l(1 - z_l) \leq f^{\mathrm{redi}}_{t,l,\mathrm{s}} - B_l(\theta_{t,n,\mathrm{s}} - \theta_{t,j,\mathrm{s}}) \leq M_l(1 - z_l) \tag{10}$$

for all $l = (n,j) \in L^{\mathrm{new}}, t \in T, \mathrm{s} \in \mathrm{S}$, where M_l is a sufficiently large number.

To obtain unique physical solutions, we fix the voltage angle at an arbitrary node $\hat{n} \in N$:

$$\theta_{t,\hat{n},\mathrm{s}} = 0 \quad \text{for all } t \in T, \mathrm{s} \in \mathrm{S}. \tag{11}$$

Furthermore, the power flow on all lines is restricted by the thermal capacity:

$$- \bar{f}_l \leq f^{\mathrm{redi}}_{t,l,\mathrm{s}} \leq \bar{f}_l \quad \text{for all } l \in L^{\mathrm{ex}}, t \in T, \mathrm{s} \in \mathrm{S} \tag{12}$$

$$- z_l \bar{f}_l \leq f^{\mathrm{redi}}_{t,l,\mathrm{s}} \leq z_l \bar{f}_l \quad \text{for all } l \in L^{\mathrm{new}}, t \in T, \mathrm{s} \in \mathrm{S}. \tag{13}$$

Applying generation capacity limits and variable bounds analogously to level two, we obtain the following third-level problem formulation:

$$\min_{y^{\mathrm{redi}}_{t,g,\mathrm{s}}} \quad \psi_{3,\mathrm{s}} \quad \text{s.t.} \quad (1), (6), (8), (9)\text{–}(13),$$

where we replaced $y^{\mathrm{spot}}_{t,g,\mathrm{s}}$ in (1) and (6) by the redispatch variables $y^{\mathrm{redi}}_{t,g,\mathrm{s}}$ and the set G^{priv}_n by G^{all}_n. We obtain a linear minimization problem over linear constraints.

3.6. **Model discussion and solution approach.** Considering all three levels, we obtain a mixed-integer nonlinear trilevel optimization model. In this section, we describe how we transform the model to an equivalent bilevel problem and solve the reformulated model to global optimality. Figure 3 illustrates the general structure of the model in technical terms, where X_i and $W_{i,s}$ are deterministic and random variables, respectively, of level i, and Ω_i and $\Psi_{i,s}$ denote the feasible sets of X_i and $W_{i,s}$, respectively, of level i.

FIGURE 3. Schematic representation of the trilevel market model

$$\begin{aligned} \max_{X_1} \quad & \psi_1(X_1, X_2) + \mathbb{E}_s\left[\psi_1(W_{2,s}, W_{3,s})\right] \\ \text{s.t.} \quad & X_1 \in \Omega_1, \\ & \max_{X_2, W_{2,s}} \quad \psi_2(X_2) + \mathbb{E}_s\left[\psi_2(W_{2,s})\right] \\ & \quad \text{s.t.} \quad (X_1, X_2) \in \Omega_2, \\ & \quad \phantom{\text{s.t.}} \quad W_{2,s} \in \Psi_{2,s} \quad \text{for all } \mathrm{s} \in \mathrm{S}, \\ & \quad \quad \min_{W_{3,s}} \quad \psi_{3,\mathrm{s}}(W_{2,s}, W_{3,s}) \\ & \quad \quad \text{s.t.} \quad (W_{2,s}, W_{3,s}) \in \Psi_{3,s} \quad \text{for all } \mathrm{s} \in \mathrm{S} \end{aligned}$$

In general, such multilevel mixed-integer nonlinear models are intractable (Dempe et al. 2015). To be able to solve instances of relevant sizes, problem-tailored solution approaches need to be developed. Therefore, we exploit the specific problem structure of our model to reformulate the trilevel market model as an equivalent mixed-integer bilevel model with concave-quadratic objectives at both levels. We adapt the reformulation used for a similar setting in Grimm et al. (2016a) to apply it to the stochastic model formulation. This reformulation builds upon the weak coupling of the trilevel model as described in Section 2.2. Level 2 only depends on discrete line investment variables of the first level for two reasons: first, only the

TSO carries out investment in and dispatch of backup capacity, in case redispatch of private generation capacity does not suffice. Thus, backup does not affect spot market decisions. Second, we assume cost-based redispatch, which means that firms do not receive additional rents in the third stage. Consequently, the interconnection of level 2 and 3 is purely driven by line investment variables from level 1.

We exploit this weak coupling by decomposing our model in the following way: we fix line investment variables in the second level and solve it for every possible realization of line investment scenarios.

Note that uniqueness of the solution for given line investment is not ensured in case generation technologies have the same investment and production costs (Grimm et al. 2017). In order to ensure a unique solution of the level 2 problem, we apply the following tie-breaking rule: in case several generators in one bidding zone have the same investment and production costs, investment in this technology across all nodes in the zone is divided proportionally to the maximum capacity allowed at node $n \in N$. In case there is no upper limit, investment is simply divided up equally across all nodes in the respective zone. Analogously, production is divided proportionally to the capacity at node $n \in N$ in case there are generators with the same variable production cost in one zone.

We then insert spot market outcomes into level 1 and 3 to compute the remaining first- and third level solutions that do not affect spot market outcomes. We thus end up with a master problem consisting of the first and the third level with a reduced number of variables, and a single-level sub-problem consisting of level 2. We now show how the master problem can be transformed into a single-level problem and thus be solved efficiently. To this end, we use the following model property. Consider the objective functions ψ_1 and $\psi_{3,s}$ of level 1 and 3, respectively. It holds that

$$\psi_1 = \sum_{\mathrm{s}\in \mathrm{S}} \pi_{\mathrm{s}} \left(-\psi_{3,s} + \sum_{n\in N}\sum_{t\in T}\Big(\int_0^{d_{t,n,s}} p_{t,n,\mathrm{s}}(\xi)\,\mathrm{d}\xi - \sum_{g\in G_n^{\mathrm{all}}} c_g^{\mathrm{var}} y_{t,g,\mathrm{s}}^{\mathrm{spot}}\Big)\right) - \sum_{n\in N}\sum_{g\in G_n^{\mathrm{all}}} c_g^{\mathrm{inv}}\bar{y}_g - \sum_{l\in L^{\mathrm{new}}} c_l^{\mathrm{inv}} z_l. \tag{14}$$

Equation (14) reveals that the objective functions of level 1 and 3 differ by a term that only depends on first- and second-level variables, i.e., line investment and spot market variables. More explicitly, this implies that the first- and the third-level problems have affine equivalent objective functions and thus have identical optimization directions. Therefore, we can reformulate the original trilevel model into the following equivalent bilevel model:

$$\begin{aligned} \max \quad & \psi_1(X_1, X_2) + \mathbb{E}_s\left[\psi_1(W_{2,s}, W_{3,s})\right] \qquad (15)\\ \text{s.t.} \quad & X_1 \in \Omega_1, (W_{2,s}, W_{3,s}) \in \Psi_{3,s} \quad \text{for all s} \in \mathrm{S},\\ & (X_1, X_2, W_{2,s}) \in arg\,max\{\psi_2(X_2) + \mathbb{E}_s\left[\psi_2(W_{2,s})\right] : (X_1, X_2) \in \Omega_2,\\ & W_{2,s} \in \Psi_{2,s} \quad \text{for all s} \in \mathrm{S}\}. \end{aligned}$$

As shown in (15), the master- and the sub-problem are only coupled by transmission line investment. Fixing these variables yields decoupled models that can be solved separately. As line investment $z_l \in \{0,1\}, l \in L^{\mathrm{new}}$ is discrete, we iterate over all possible line investment scenarios.[1] The detailed reformulated bilevel problem can be found in Appendix B.

[1] In a slightly modified setting, Grimm et al. (2019) furthermore propose replacing the resulting bilevel problem by an equivalent single-level problem using a Karush-Kuhn-Tucker (KKT) reformulation for the lower level (Dempe and Zemkoho 2013), which can be solved with standard solvers. It has been shown, however, that this approach leads to a numerically more complicated

4. Two-node example

The model as well as the iterative solution method described in Section 3 have been implemented in General Algebraic Modeling System (GAMS) Release 25.1.3 (GAMS Development Corporation 2018). All models that need to be solved are either mixed integer quadratic programs or linear programs and were solved with Gurobi 8.1.0 (Gurobi Optimization 2019).

In this section, the effect of regulatory uncertainty on investment decisions, welfare levels, electricity prices, distribution of rents, and expected profits is addressed in a stylized two-node example. We consider two possible scenarios on market design: one, in which the market consists of a single bidding zone, including both nodes; and a second scenario, in which the market is divided into two bidding zones and each node represents one of the two zones. There is regulatory uncertainty for market participants regarding which of the two market designs will be implemented. This uncertainty is parametrized through a common probability distribution of market participants over the possible designs of bidding zones. To show the effect of regulatory uncertainty in a system with different levels of renewables investment, we set up two sets of input data with a low and high CO_2 allowance price, respectively:

i) case A with a moderate CO_2 allowance price of 15 €/t,
ii) case B with a higher CO_2 allowance price of 35 €/t.

Note that in each case, both nodes face the same allowance price.

4.1. Operating points for demand and generation.

Applying a greenfield approach, we do not account for any existing capacity. All quantitative values in the two-node example refer to a system peak demand of 1 MW, whereof node 1 has a demand share of 30% compared to 70% at node 2 (see Figure 4). The temporal resolution has 400 operating points, which occur at different frequency and scale to one representative year: there are two seasons (winter and summer) with forty different demand levels each, t_1 (highest winter peak) to t_{40} (lowest winter off-peak) and t_{41} (highest summer peak) to t_{80} (lowest summer off-peak). These multiply with five different availability levels for wind power, w_1 (highest) to w_5 (lowest). Table 1 states the respective frequency of the operating points, while Table 4 in Appendix A provides a reference demand level, a reference price, and an availability factor for wind power for each operating point. Linear demand functions at each node are then derived for each operating point with the help of reference demand, reference price, and a point elasticity of demand ($\epsilon = -0.1$).

Table 1. Structure of operating points with respective frequency

	No	Entries (frequency)
Seasons	2	winter (0.5), summer (0.5)
Hours	40	t_1–t_{40} (0.0125)
Wind	5	w_1 (0.05), w_2 (0.2), w_3 (0.5), w_4 (0.2), w_5 (0.05)

4.2. Economic parameters for generation technologies.

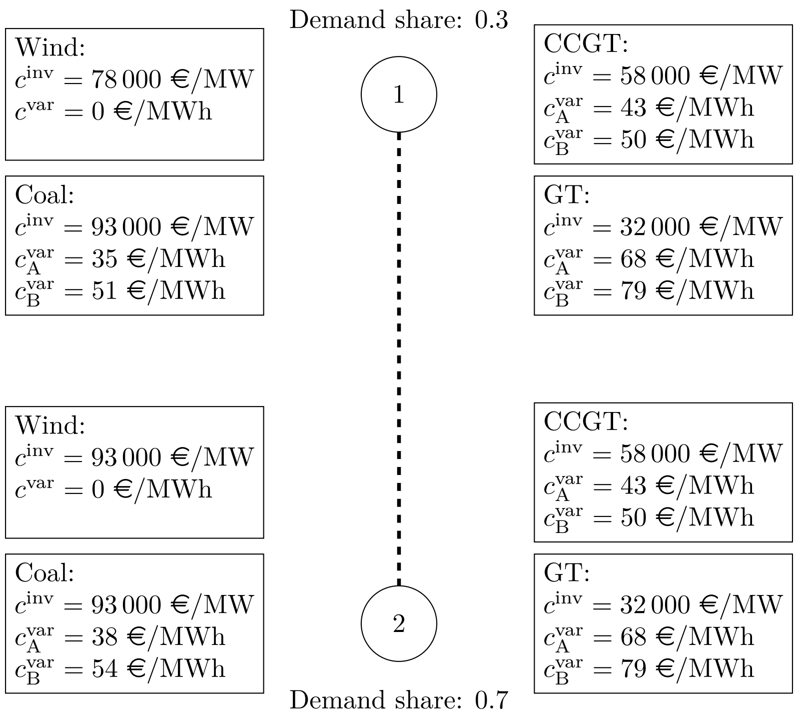
The economic parameters in Figure 4 state the annualized investment costs $c_c^{\text{inv}} > 0$ and variable generation costs $c_c^{\text{var}} \geq 0$ of wind power and conventional power stations fired by coal and natural gas (i.e., combined-cycle gas turbines (CCGT) and gas turbines (GT))

single-level model with long computation times, which was also the case for our model setup. Note that, as both methods yield globally optimal solutions, the same results are obtained in both cases.

in case $c \in \{A,B\}$.[2,3] Coal and wind power plants have the highest fixed costs, followed by CCGT and GT. The assumption of worse wind conditions at node 2 is represented with a markup on investment costs, whereas both nodes have equal availability factors (i.e., the same generation pattern) for one operating point.

The different levels of the CO_2 prices affect the variable generation costs of conventional power plants, whereas wind power always has variable costs of zero. We further assume that coal is more expensive at node 2 (e.g., due to an additional markup for regional coal transport), resulting in higher variable costs of coal generation compared to node 1. In case A, the conventional technology with lowest variable generation costs is coal, followed by CCGT, and GT. In case B, which implies a higher CO_2 price, generation companies choose between CCGT (always being more profitable than coal), GT, and wind power plants.

FIGURE 4. Illustration of two-node example with annualized investment costs c_c^{inv} and variable generation costs c_c^{var}



4.3. **Network expansion.** The TSO can invest in line capacity between node 1 and node 2 in incremental steps of 0.01 MW. Annualized fixed costs for transmission investment of 1 MW are 25,000 €.

[2]To calculate annualized investment costs, we assume overnight investment costs of 1 600 T€/MW for coal, 1 000 T€/MW for CCGT, 500 T€/MW for GT, and 1 200 T€/MW for wind at node 1 (1 440 T€/MW at node 2 including a markup of +20%). We further assume depreciation periods of 40 years for coal and CCGT and 30 years for GT and wind power plants and an interest rate of 5%. As an alternative to load shedding, the TSO has the possibility to contract capacity of GT outside the spot market at the same investment and variable costs.

[3]Variable generation costs of conventional technologies follow these assumptions: a hard coal price of 85.0 €/t (about 10.4 €/MWh$_{th}$), a natural gas price of 21 €/MWh$_{th}$, and a price for CO_2 emission allowances of 15 €/t for case A and 35 €/t for case B. Efficiency factors are 45% for coal, 55% for CCGT, and 35% for GT, resulting in specific CO_2 emissions of 800 g/kWh$_{el}$ for coal, 340 g/kWh$_{el}$ for CCGT, and 535 g/kWh$_{el}$ for GT.

5. Results

In the following, we discuss to what extent regulatory uncertainty affects level and distribution of investments, welfare, prices, and profits. We take the perspective that one bidding zone is in place and there is uncertainty about whether or not it will be split into two zones in the future. Of course, the reasoning would also be possible vice versa with the possibility to reduce the number of bidding zones.[4] We evaluate the model for a discrete set of probabilities that market participants (the TSO and private investors) assume for the implementation of two bidding zones, i.e., $P(k = 2) \in \{0, 0.1, \ldots, 1\}$. In order to keep runtimes short, we do not increase the resolution any further, as this would not significantly change the results. Market participants expect the implementation of either one or two bidding zones, i.e. $P(k = 1) + P(k = 2) = 1$. When $P(k = 2) = 0.0$, market participants are certain to see one bidding zone in the future, whereas for $P(k = 2) = 1.0$, they are certain that two bidding zones will be in place.

5.1. Investment in generation and transmission.

Result 1. *Expectations that the market design changes from one to two bidding zones affect the location as well as the technology of generation capacity and also the level of transmission capacity. Consequently, not only the implementation but also the expectation of zonal reconfiguration has quantifiable economic effects.*

Figure 5 (case A) and Figure 6 (case B) give an overview on decisions on investment in generation and transmission capacity for different probabilities. At this point, results only depend on the expectation to end up with either one or two bidding zones and not on the later choice on the bidding zone design by the regulator.

For $P(k = 2) = 0.0$, gas-fired power plants are equally distributed across both nodes according to the tie-breaking rule in the model description. This is an exogenous assumption following their equal investment and variable production cost throughout all nodes. In contrast, wind power plants have regionally differentiated investment costs and coal power plants have regionally differentiated variable costs. In expectation of one bidding zone, generation companies invest in wind and coal capacity only at node 1 due to their lower nodal costs. While case A sees a combination of coal and wind power, the higher CO_2 price in case B leads to more investment in wind power and CCGT but none in coal-fired power plants. Overall investment in generation capacity is higher in case B (2.23 MW) compared to case A (1.58 MW) due to the low guaranteed availability of wind capacity.

For $P(k = 2) = 1.0$, locally differentiated spot market prices reflect spatial scarcities. The TSO anticipates that its investment decision on the level of transmission capacity alters investment decisions of generation companies. As a result, the TSO reduces its investment in transmission capacity to about 55% of the initial level. With the expectation of two bidding zones, generation investment in gas-fired power plants shifts to a large extent to node 2 and increases for CCGT, while investment in coal and wind power plants decreases at node 1. Further, node 2 receives a small share of investment in coal capacity (case A) and wind capacity (case B).

For case A, Figure 5 summarizes investment decisions for different values of $P(k = 2)$.[5] We observe that assigning even a relatively small probability to two bidding zones provides incentives for the relocation of most gas-fired generation capacity to node 2. The reason is that gas-fired power plants have the same investment

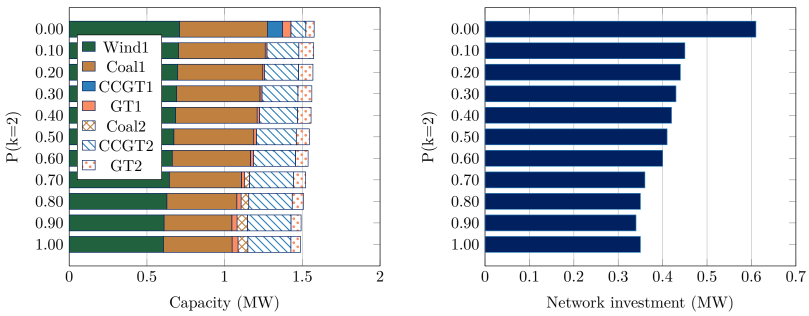
[4] An example are the entry-exit zones in European gas markets with an ongoing development of bidding zone reductions.

[5] For $0 < P(k = 2) < 1$, the TSO contracts backup capacity of about 0.01 MW at node 2.

and variable costs at both nodes. Therefore, even a very low probability for the occurrence of two bidding zones eliminates the indifference and incentivizes a shift of investment to node 2, where electricity prices are higher in the case of two bidding zones. The majority of coal and all wind power plants, which have a more favorable cost structure at node 1, are located at node 1 for all $P(k = 2) \in \{0, 0.1, \ldots, 1\}$. For an increasing probability up to $P(k = 2) \leq 0.6$, coal and wind capacity at node 1 slightly decreases compared to the benchmark ($P(k = 2) = 0.0$), while more CCGT capacity is built at node 2. Only for $P(k = 2) \geq 0.7$, generation companies invest in small amounts of coal capacity at node 2. In general, the capacity of coal and wind power plants decreases for higher probabilities $P(k = 2)$, while CCGT capacity increases, leading not only to a different locational distribution, but also to a change in technology.

The relocation of generation capacity closer to load centers at node 2, already for $P(k = 2) = 0.1$, goes along with significant reductions in transmission investment. Except for the initial reduction from 0.61 MW to 0.45 MW at $P(k = 2) = 0.1$ and a small step with the relocation of some coal capacity to node 2 at $P(k = 2) = 0.7$, transmission capacity decreases steadily for increasing $P(k = 2)$, reaching 0.35 MW at $P(k = 2) = 1.0$.

FIGURE 5. Generation and network capacity (case A)



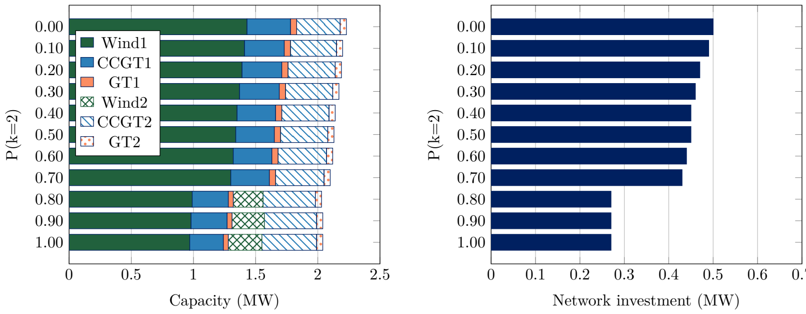
(a) Capacity investment (b) Transmission investment

In case B (Figure 6), wind power is the technology with lowest average generation costs and generation companies invest in 1.43 MW of wind power plants at node 1 for $P(k = 2) = 0.0$. Due to its varying availability, the installed wind capacity does not supply the entire electricity demand in all operating points, resulting in additional investment in CCGT and GT capacity. Compared to case A, higher overall CCGT investment leads to more generation capacity at node 2 after tie-breaking investment to both nodes at $P(k = 2) = 0.0$. Together with the complementary character in the utilization of network capacity for wind and CCGT at node 1, this allows for lower investment in transmission capacity.

Compared to case A, low probabilities for $P(k = 2)$ only have a minor impact on investment in generation and transmission capacity. Some gas-fired capacity is relocated to node 2 but the effect is less prominent. For increasing $P(k = 2)$, wind capacity at node 1 constantly reduces to 1.30 MW at $P(k = 2) = 0.7$, decreasing overall installed generation capacity. At $P(k = 2) = 0.8$, a structural change takes place as investment in wind power capacity at node 2 (0.24 MW) replaces some wind power capacity at node 1 (0.31 MW). Even higher $P(k = 2)$ imply an additional, yet small relocation of wind power from node 1 to node 2, resulting in total wind power capacity of 1.24 MW for $P(k = 2) = 1.0$.

Transmission investment decreases monotonically, yet on limited scale from 0.50 MW to 0.43 MW until $P(k = 2) = 0.7$ and only at $P(k = 2) = 0.8$ it substantially decreases to 0.27 MW. Again, higher probabilities $P(k = 2)$ entail an altered regional distribution and a change in technology for generation investment with less wind and more CCGT in the generation mix.

FIGURE 6. Generation and network capacity (case B)



(a) Capacity investment (b) Transmission investment

5.2. Market results.

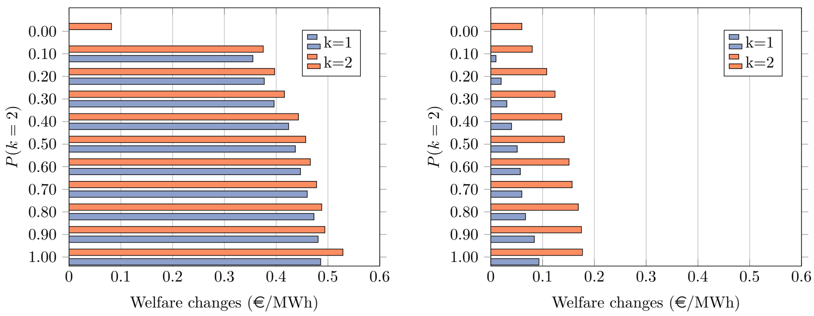
Result 2. *In case of regulatory uncertainty, a perceived positive probability of zonal reconfiguration from one to two bidding zones leads to welfare gains independently from the regulator's ultimate decision on the zonal configuration. This is mainly due to more efficient long-run investment decisions that anticipate a possible change of the market design. Importantly, this anticipation effect reduces possible additional welfare gains upon the actual implementation of two bidding zones considerably.*

Welfare effects. Figure 7 illustrates welfare changes after the implementation of one or two bidding zones as compared to a benchmark scenario, where one zone is anticipated and also implemented. General results for both cases are, that introducing two bidding zones without any anticipation by market participants yields comparably low welfare gains. A strictly positive expectation of two bidding zones by the TSO and generation companies leads to a higher welfare level, in which case the implementation of two bidding zones yields additional welfare gains. Highest welfare levels result from $P(k = 2) = 1.0$ and $k = 2$, due to the right assumption of the TSO and generation companies on the implemented bidding zone design, when deciding on investment, combined with a more efficient market dispatch after the implementation of two bidding zones.

For case A, even a relatively low probability for implementing two zones already leads to high welfare gains, mainly due a more efficient relocation of CCGT and GT capacity (at no additional cost) and less network investment. Probabilities $P(k = 2) > 0.1$ lead to additional monotonically increasing welfare gains with respect to the benchmark scenario. We also observe that for a given probability $P(k = 2)$, welfare gains with respect to the benchmark case are relatively similar for $k = 1$ and $k = 2$. This indicates that most welfare gains result from changes in transmission and generation investment (taken under uncertainty), while the later decision by the regulator for either one or two bidding zones has limited effects on welfare.

In case B, welfare gains from investment decisions are significantly lower than in case A (with respect to the benchmark case), as investment for $P(k = 2) = 0.0$ is already more efficient with higher levels of gas-fired capacity at node 2 and less network investment. Instead, the welfare gains following the implementation of two zones ($k = 2$) are several times higher than in case A for a given probability $P(k = 2) > 0$. This illustrates that welfare gains only partly occur due to a more efficient location of generation capacity, and a large part depends on regionally efficient market results during spot market trading.

FIGURE 7. Welfare for implementation one and two bidding zones
A value of 1 €/MWh translates into annual welfare gains of 1 million € for 1 TWh in annual electricity demand



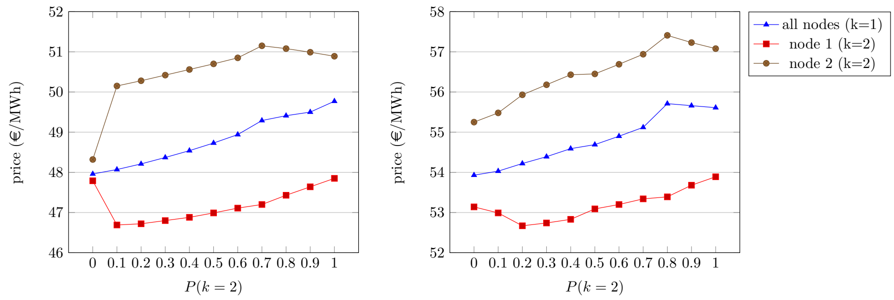
(a) Case A (b) Case B

Spot market prices. With higher expectations for two bidding zones, average spot market prices mostly increase (Figure 8) while network fees decrease (Figure 9).

With the implementation of one bidding zone (k=1), investment decisions (taken in anticipation of two bidding zones) increase electricity spot market prices by almost 2 €/MWh in both cases for high values of $P(k = 2)$. While consumers in case A can more than compensate the additional expenses in the spot market with lower network fees for low $P(k = 2)$, this does not hold for higher probabilities and in case B.

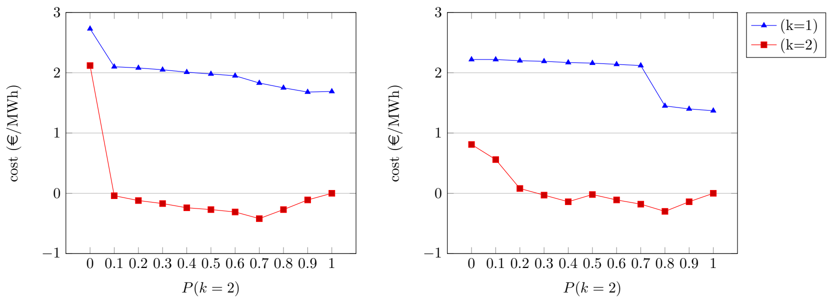
With the implementation of two bidding zones (k=2), spot market prices are 1-2 €/MWh lower (higher) at node 1 (node 2) compared to the implementation of one bidding zone. Reasons are the change from technologies with lower variable production cost at node 1 to technologies with higher variable costs closer to the demand center at node 2 and a reduction in network investment. This leads to network constraints and zonal price differences in some operating points. The general price trend is upwards for an increasing expectation to see two bidding zones. Exceptions are, that node 1 sees a drop in average spot market prices for low $P(k = 2)$ and prices at node 2 start to decrease for high $P(k = 2)$ which reduces price spreads. Compared to the benchmark scenario, network fees decline steeply for low $P(k = 2) \leq 0.2$, reach even negative levels for higher $P(k = 2)$ by collecting congestion rents on trade between the two zones, and settle at 0 €/MWh for $P(k = 2) = 1$.

FIGURE 8. Average, demand-weighted spot market prices



(a) Case A (b) Case B

FIGURE 9. Additional network fees including network costs, balancing cost, and network congestion rents



(a) Case A (b) Case B

5.3. **Distributional effects.**

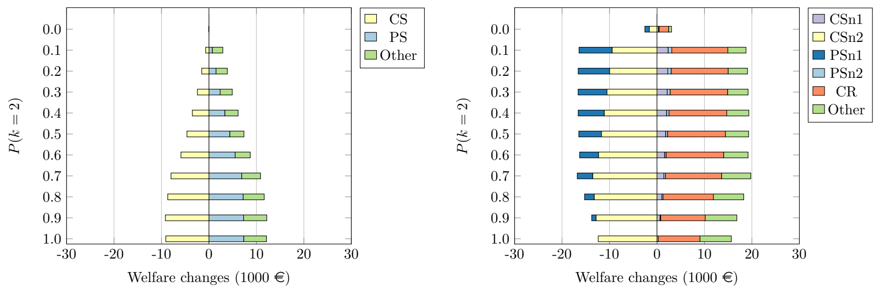
Result 3. *Regulatory uncertainty leads to distributional effects (as compared to the case without regulatory uncertainty) that are due to its effect on investment decisions and, thus, market outcomes. In particular generation technologies with relatively high investment costs are prone to economic risk.*

Stakeholder rents. Figures 10–11 show the different welfare components in more detail. With the implementation of one bidding zone, consumer surplus decreases and producer surplus increases with higher probabilities for $P(k = 2)$. The reason is the change in technology from coal and wind at node 1 to CCGT at node 2 (see Section 5.1) at higher probabilities for two bidding zones. Electricity generation becomes more expensive (prices go up) while overall costs for transmission infrastructure and redispatch decreases (positive other welfare gains). In case B, the positive other effects only realize at $P(k = 2) \geq 0.8$, when some wind is relocated to node 2 and transmission investment decreases.

With the implementation of two bidding zones, prices at node 1 decrease and consumer surplus is higher (producer surplus lower) than in the benchmark case $P(k = 2) = 0.0$. In contrast, consumer surplus is lower (producer surplus higher) at node 2 than in the benchmark case, as prices go up due to investment in generation capacity with higher variable cost. Losses for consumers at node 2 and producers at node 1 are significantly higher than gains by consumers at node 1 and producers at node 2. Also, as producers adapt to two bidding zones with higher $P(k = 2)$, welfare losses mostly allocate to consumers at node 2. On the other hand, most welfare gains materialize in lower network and redispatch costs (other) and a significant amount of congestion rents (CR).

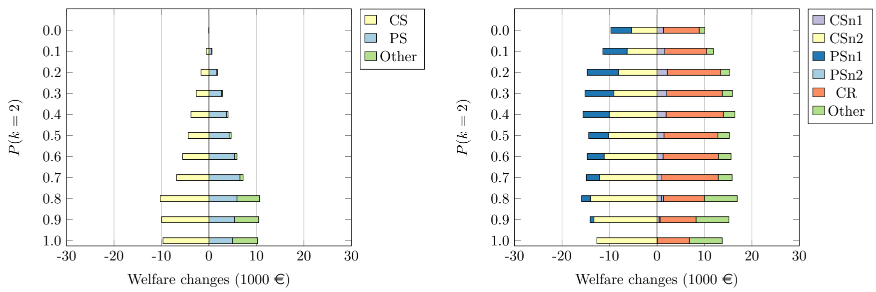
The general distributional effects are the same for case A and case B, although in case A it is more pronounced due to higher price differences with the initial relocation of gas-fired power plants for low $P(k = 2)$. Distribution effects are also generally lower if stakeholders anticipate a zonal design correctly and with a high probability.

FIGURE 10. Welfare distribution in case A



(a) Realization: One zone (b) Realization: Two zones

FIGURE 11. Welfare distribution in case B



(a) Realization: One zone (b) Realization: Two zones

Technology profits. Generation companies make their investment decision according to their probability distribution on the expected bidding zone configuration. Under the assumption of perfect competition, investments in all technologies at both nodes receive zero profits in market equilibrium. This no longer holds for investments under uncertainty after the implementation of either one or two bidding zones. Table 2 for case A and Table 3 for case B provide profits and losses by technology for different probabilities.

For a positive expectation of market participants to see two bidding zones and the later implementation of one bidding zone, technologies make a profit at node 1 and a loss at node 2. Vice versa, some technologies make losses at node 1 and profits at node 2 with the implementation of two bidding zones. For each technology at one node, the sum of profits and losses multiplied with the respective probabilities $P(k = 1)$ and $P(k = 2)$ result in an expected profit of zero.

For the implementation of one bidding zone in case A, coal and wind generators are better off at node 1 as compared to the benchmark, whereas coal and CCGT at node 2 are worse off (and vice versa for two bidding zones). Most exposed is wind, followed by coal at node 1, coal at node 2, and CCGT at node 2. In case B, wind power is exposed to uncertainty with almost twice the possible profits and losses than in case A, while there is no effect on CCGT capacity at both nodes. The results indicate, that price differences due to network constraints do not occur in operating points with peak prices as not GT but technologies with lower variable costs are exposed to risks. In case A this includes wind, coal, and CCGT while in case B it only affects wind.

Table 2. Generators' profit for uncertain bidding zones (case A)

€/MWh	One zone				Two zones			
P(k=2)	wind_{n1}	coal_{n1}	coal_{n2}	CCGT_{n2}	wind_{n1}	coal_{n1}	coal_{n2}	CCGT_{n2}
0.0	0.00	0.00	-	0.00	-0.28	-0.14	-	0.49
0.1	0.14	0.14	-	-0.15	-1.30	-1.27	-	1.09
0.2	0.31	0.29	-	-0.28	-1.26	-1.22	-	0.89
0.3	0.50	0.46	-	-0.38	-1.18	-1.13	-	0.71
0.4	0.73	0.65	-	-0.46	-1.09	-1.03	-	0.55
0.5	0.98	0.86	-	-0.51	-0.98	-0.91	-	0.41
0.6	1.27	1.08	-	-0.54	-0.85	-0.76	-	0.29
0.7	1.77	1.43	-1.23	-0.57	-0.76	-0.66	0.41	0.20
0.8	2.01	1.53	-1.22	-0.60	-0.50	-0.41	0.25	0.12
0.9	2.22	1.59	-1.20	-0.65	-0.25	-0.19	0.11	0.06
1.0	2.22	1.57	-1.23	-0.62	0.00	0.00	0.00	0.00

Table 3. Generators' profit for uncertain bidding zones (case B)

€/MWh	One zone		Two zones	
P(k=2)	wind_{n1}	wind_{n2}	wind_{n1}	wind_{n2}
0.0	0.00	-	-1.67	-
0.1	0.22	-	-1.98	-
0.2	0.64	-	-2.59	-
0.3	1.03	-	-2.43	-
0.4	1.47	-	-2.23	-
0.5	1.70	-	-1.72	-
0.6	2.18	-	-1.47	-
0.7	2.69	-	-1.17	-
0.8	4.10	-3.91	-1.05	0.95
0.9	3.98	-4.03	-0.45	0.43
1.0	3.82	-4.31	0.00	0.00

6. Discussion

The observations above highlight several key insights. First of all, our analysis shows that expectations about future market design are crucially important. In some cases, even a small probability of a change in the bidding zone configuration is enough to significantly change investment levels and realize a significant part of the benefits of an actual market design change. This is particularly true if generation investment and operational costs are not highly location-dependent, because in this case, a small probability of price divergence will tip the balance in favor of one location. If the costs of generation are location-dependent, as they are for, e.g., wind generators, this effect is much less pronounced. In this case, a significant probability of diverging prices is necessary to overcome cost difference between the different locations. In addition, if the available generation capacity varies over time, as it does for most renewables, a probability of a market design change also has less of an impact on welfare, as in this case a more efficient distribution of investment is not enough – the actual change to a market design which allows for a more efficient dispatch has significant additional benefits.

Although expectations about market design change welfare, they also have distributional effects. In the short term, an increase in the perceived probability of a change in market design generally decreases consumer surplus, as it leads to higher prices. However, this is offset by a decrease in network costs, which are usually indirectly paid for by consumers in the longer run. Different expectations also influence how the additional gains from an actual change in market design are distributed among consumers and producers at different locations. There are also distributional effects between different generation technologies. Generators with higher investment costs are most exposed to our type of regulatory uncertainty.

Our analysis also shows that structural regulatory uncertainty is fundamentally different from parametric uncertainty about demand, costs, and other parameters that are usually included in stochastic models. While the latter uncertainties usually have a negative effect, increasing system costs and decreasing welfare in comparison to a situation in which the parameters are known, structural regulatory uncertainty can have a positive effect. This is only the case if there is probability that market design will become more efficient. It is also not universally true; for instance, if investors are risk averse, structural regulatory uncertainty may discourage investment to the point where welfare is negatively affected. Nevertheless, as we have shown above, there is a possibility that regulatory uncertainty increases welfare.

Importantly, this does not mean regulatory uncertainty can be used as a long-term policy tool, as expectations cannot consistently diverge from reality. It is, however, something that policy makers and regulators should be aware of, as regulatory uncertainty can have a significant impact on markets. In our particular example, if market participants believe that there is a nonzero probability of a change from uniform to zonal pricing, part of the benefits from this change are already realized, regardless of whether or not it actually happens. This implies that the actual benefits of a change in market design may be lower than expected. Importantly, it also implies that as long as policy makers are themselves unsure about policies that increase market efficiency, they should not try to shut down the wide debate about these, as this debate may already have positive effects.

Naturally, our approach has limitations. We have considered a small model in which market design is the only source of uncertainty. In the real world, there is additional uncertainty about a wide range of other variables and structures. There are also other market inefficiencies. All of this means that the additional effect of regulatory uncertainty may be smaller. In addition, we assume that market participants are risk-neutral. In reality, market participants are likely to be risk averse, which will increase the impact of uncertainty on investment levels and spatial distributions. Finally, in our model, we only have one investment stage. This may overstate the impact of uncertainty on investment, as compared to a situation in which investments are made continuously, with options to wait or adjust.

All these issues are worth investigating further. Nevertheless, we expect our qualitative findings to carry over to larger, more complex, and more realistic settings.

7. Conclusion

In this paper, we have developed a novel method for including structural regulatory uncertainty about market design in a multilevel electricity market model with transmission and generation investment and have applied it to a stylized two node example studying the effect of uncertainty on market outcomes.

This analysis yields various insights. First, our qualitative results show that some of the welfare gain from a switch to a more efficient market design might already be realized before the actual implementation, if market participants anticipate the market design change. Market participants' beliefs about future bidding zones should therefore not be ignored in the discussion on bidding zone topology. Second, even small probabilities for the expectation of a change in market design can lead to more efficient generation and transmission investment. The welfare gains increase with higher expectations of a switch to a more efficient system. Third, we observe that risk is not distributed equally between market participants: in general, generators with high investment costs carry the risk of investing not the right quantity and in the wrong locations, while generators with lower investment costs are not affected negatively by uncertainty.

When considering implementing a change to a more efficient market design, policy makers should be aware of the fact that part of the welfare gains might already have been realized due to a period of uncertainty preceding the actual implementation. At the same time, deliberately inducing uncertainty cannot be used as a policy tool by the regulators in the long run, as expectations and realizations cannot indefinitely diverge.

To adequately assess and disentangle the different effects of uncertainty, we have applied our model to a small network with simplifying assumptions. Future work could address a more realistic representation of an existing electricity system, to quantify results and verify that they carry over to real-world networks.

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References

Ambrosius, Mirjam, Veronika Grimm, Thomas Kleinert, Frauke Liers, Martin Schmidt, and Gregor Zöttl (2018). "Endogenous Price Zones and Investment Incentives in Electricity Markets: An Application of Multilevel Optimization with Graph Partitioning." In: *Optimization Online*. Preprint. URL: http://www.optimization-online.org/DB_FILE/2018/10/6868.pdf.

Baringo, Luis and Antonio J. Conejo (2013). "Risk-Constrained Multi-Stage Wind Power Investment." In: *IEEE Transactions on Power Systems* 28.1, pp. 401–411. DOI: 10.1109/TPWRS.2012.2205411.

Bertsch, Joachim, Tom Brown, Simeon Hagspiel, and Lisa Just (2017). "The relevance of grid expansion under zonal markets." In: *The Energy Journal* 38.1. DOI: 10.5547/01956574.38.5.jber.

Birge, John R. and François Louveaux (2011). *Introduction to Stochastic Programming*. Springer Series in Operations Research and Financial Engineering. New York, NY: Springer New York. DOI: 10.1007/978-1-4614-0237-4.

Boucher, Jacqueline and Yves Smeers (2001). "Alternative Models of Restructured Electricity Systems, Part 1: No Market Power." In: *Operations Research* 49.6, pp. 821–838. DOI: 10.1287/opre.49.6.821.10017.

CMA (2015). *Locational Pricing in the Electricity Market in Great Britain*. Competition and Markets Authority, London. URL: https://assets.publishing.service.gov.uk/media/54eb5da5ed915d0cf7000010/Locational_pricing.pdf.

Conejo, Antonio J., Miguel Carrión, and Juan M. Morales (2010). *Decision Making Under Uncertainty in Electricity Markets*. Vol. 153. International Series in Operations Research & Management Science. Boston, MA: Springer US. DOI: 10.1007/978-1-4419-7421-1.

Daxhelet, Olivier. and Yves Smeers (2007). "The EU regulation on cross-border trade of electricity: A two-stage equilibrium model." In: *European Journal of Operational Research* 181.3, pp. 1396–1412. DOI: 10.1016/j.ejor.2005.12.040.

Dempe, Stephan, Vyacheslav Kalashnikov, Gerardo A. Pérez-Valdés, and Nataliya Kalashnykova (2015). *Bilevel Programming Problems*. Energy Systems. Berlin, Heidelberg: Springer Berlin Heidelberg. DOI: 10.1007/978-3-662-45827-3.

Dempe, Stephan and Alain B. Zemkoho (2013). "The bilevel programming problem: reformulations, constraint qualifications and optimality conditions." en. In: *Mathematical Programming* 138.1-2, pp. 447–473. DOI: 10.1007/s10107-011-0508-5.

Egerer, Jonas, Jens Weibezahn, and Hauke Hermann (2016). "Two price zones for the German electricity market — Market implications and distributional effects." In: *Energy Economics* 59, pp. 365–381. DOI: 10.1016/j.eneco.2016.08.002.

Ehrenmann, Andreas and Yves Smeers (2011). "Generation Capacity Expansion in a Risky Environment: A Stochastic Equilibrium Analysis." en. In: *Operations Research* 59.6, pp. 1332–1346. DOI: 10.1287/opre.1110.0992.

ENTSO-E (2018). *First edition of the bidding zone review*. URL: https://docstore.entsoe.eu/Documents/News/bz-review/2018-03_First_Edition_of_the_Bidding_Zone_Review.pdf.

Frontier Economics and Consentec (2011). *Relevance of established national bidding areas for European power market integration – an approach to welfare oriented evaluation*. URL: https://www.bundesnetzagentur.de/SharedDocs/Downloads/EN/Areas/ElectricityGas/Special%20Topics/StudyPriceZone/StudyPriceZoneLong.pdf?__blob=publicationFile&v=3.

GAMS Development Corporation (2018). *General Algebraic Modeling System (GAMS) Release 27.1.0*.

Grimm, Veronika, Thomas Kleinert, Frauke Liers, Martin Schmidt, and Gregor Zöttl (2019). "Optimal price zones of electricity markets: a mixed-integer multilevel model and global solution approaches." en. In: *Optimization Methods and Software* 34.2, pp. 406–436. DOI: 10.1080/10556788.2017.1401069.

Grimm, Veronika, Alexander Martin, Martin Schmidt, Martin Weibelzahl, and Gregor Zöttl (2016a). "Transmission and generation investment in electricity markets: The effects of market splitting and network fee regimes." In: *European Journal of Operational Research* 254.2, pp. 493–509. DOI: 10.1016/j.ejor.2016.03.044.

Grimm, Veronika, Alexander Martin, Martin Weibelzahl, and Gregor Zöttl (2016b). "On the long run effects of market splitting: Why more price zones might decrease welfare." In: *Energy Policy* 94, pp. 453–467. DOI: 10.1016/j.enpol.2015.11.010.

Grimm, Veronika, Lars Schewe, Martin Schmidt, and Gregor Zöttl (2017). "Uniqueness of market equilibrium on a network: A peak-load pricing approach." In: *European Journal of Operational Research* 261.3, pp. 971–983. DOI: 10.1016/j.ejor.2017.03.036.

Gurobi Optimization (2019). *Gurobi Optimizer Reference Manual*. URL: http://www.gurobi.com.

Holmberg, Pär and Ewa Lazarczyk (2015). "Comparison of congestion management techniques: Nodal, zonal and discriminatory pricing." In: *Energy Journal* 36.2, pp. 145–166. DOI: 10.5547/01956574.36.2.7.

Möst, Dominik and Dogan Keles (2010). "A survey of stochastic modelling approaches for liberalised electricity markets." In: *European Journal of Operational Research* 207.2, pp. 543–556. DOI: https://doi.org/10.1016/j.ejor.2009.11.007.

Muñoz, Francisco D., Adriaan Hendrik van der Weijde, Benjamin F. Hobbs, and Jean-Paul Watson (2017). "Does risk aversion affect transmission and generation planning? A Western North America case study." In: *Energy Economics* 64, pp. 213–225. DOI: https://doi.org/10.1016/j.eneco.2017.03.025.

Neuhoff, Karsten, Julian Barquin, Janusz W. Bialek, Rodney Boyd, Chris J. Dent, Francisco Echavarren, Thilo Grau, Christian von Hirschhausen, Benjamin F. Hobbs, Friedrich Kunz, Christian Nabe, Georgios Papaefthymiou, Christoph Weber, and Hannes Weigt (2013). "Renewable electric energy integration: Quantifying the value of design of markets for international transmission capacity." In: *Energy Economics* 40, pp. 760–772. DOI: 10.1016/j.eneco.2013.09.004.

Plancke, Glenn, Cedric De Jonghe, and Ronnie Belmans (2016). "The implications of two German price zones in a european-wide context." In: *2016 13th International Conference on the European Energy Market (EEM)*. Porto, Portugal: IEEE, pp. 1–5. DOI: 10.1109/EEM.2016.7521290.

Ruiz, Carlos and Antonio J. Conejo (2015). "Robust transmission expansion planning." en. In: *European Journal of Operational Research* 242.2, pp. 390–401. DOI: 10.1016/j.ejor.2014.10.030.

Schweppe, Fred C., Michael C. Caramanis, Richard D. Tabors, and Roger E. Bohn (1988). *Spot pricing of electricity*. Springer Science & Business Media. DOI: 10.1007/978-1-4613-1683-1.

Trepper, Katrin, Michael Bucksteeg, and Christoph Weber (2015). "Market splitting in Germany – New evidence from a three-stage numerical model of Europe." In: *Energy Policy* 87, pp. 199–215. DOI: 10.1016/j.enpol.2015.08.016.

van der Weijde, Adriaan Hendrik and Benjamin F. Hobbs (2011). "Locational-based coupling of electricity markets: benefits from coordinating unit commitment and balancing markets." In: *Journal of Regulatory Economics* 39.3, pp. 223–251. DOI: 10.1007/s11149-011-9145-4.

– (2012). "The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty." In: *Energy Economics* 34.6, pp. 2089–2101. DOI: 10.1016/j.eneco.2012.02.015.

Appendix A. Assumptions for two node example

Table 4. 80 operating points for demand with reference demand and reference price as well as a probability of 1.25% each (winter: t_1–t_{40} and summer: t_{41}–t_{80}). Five times (w_1–w_5) the 80 operating points for different wind availability (winter/summer) and with different probabilities.

Winter/Summer	Ref Demand [MW]	Ref price [EUR/MWh]	w_1 5%	w_2 20%	w_3 50%	w_4 20%	w_5 5%
t_1 / t_{41}	1.0000 / 0.9500	250 / 100					
t_2 / t_{42}	0.9750 / 0.9250	175 / 75					
t_3 / t_{43}	0.9500 / 0.9000	100 / 65					
t_4 / t_{44}	0.9250 / 0.8750	75 / 45					
t_5 / t_{45}	0.9136 / 0.8636	70 / 40					
t_6 / t_{46}	0.9023 / 0.8523	65 / 40					
t_7 / t_{47}	0.8909 / 0.8409	50 / 40					
t_8 / t_{48}	0.8795 / 0.8295	45 / 40					
t_9 / t_{49}	0.8682 / 0.8182	40 / 40					
t_{10} / t_{50}	0.8568 / 0.8068	40 / 40					
t_{11} / t_{51}	0.8455 / 0.7955	40 / 40					
t_{12} / t_{52}	0.8341 / 0.7841	40 / 40					
t_{13} / t_{53}	0.8227 / 0.7727	40 / 40					
t_{14} / t_{54}	0.8114 / 0.7614	40 / 40					
t_{15} / t_{55}	0.8000 / 0.7500	40 / 40					
t_{16} / t_{56}	0.7886 / 0.7386	40 / 40					
t_{17} / t_{57}	0.7773 / 0.7273	40 / 40					
t_{18} / t_{58}	0.7659 / 0.7159	40 / 40					
t_{19} / t_{59}	0.7545 / 0.7045	40 / 40					
t_{20} / t_{60}	0.7432 / 0.6932	40 / 40	0.81/ 0.46	0.52/ 0.34	0.22/ 0.14	0.07/ 0.04	0.02/ 0.01
t_{21} / t_{61}	0.7318 / 0.6818	40 / 40					
t_{22} / t_{62}	0.7205 / 0.6705	40 / 40					
t_{23} / t_{63}	0.7091 / 0.6591	40 / 40					
t_{24} / t_{64}	0.6977 / 0.6477	40 / 40					
t_{25} / t_{65}	0.6864 / 0.6364	40 / 40					
t_{26} / t_{66}	0.6750 / 0.6250	40 / 40					
t_{27} / t_{67}	0.6636 / 0.6136	40 / 40					
t_{28} / t_{68}	0.6523 / 0.6023	40 / 40					
t_{29} / t_{69}	0.6409 / 0.5909	40 / 40					
t_{30} / t_{70}	0.6295 / 0.5795	40 / 40					
t_{31} / t_{71}	0.6182 / 0.5682	40 / 40					
t_{32} / t_{72}	0.6068 / 0.5568	40 / 40					
t_{33} / t_{73}	0.5955 / 0.5455	40 / 40					
t_{34} / t_{74}	0.5841 / 0.5341	40 / 40					
t_{35} / t_{75}	0.5727 / 0.5227	40 / 40					
t_{36} / t_{76}	0.5614 / 0.5114	40 / 40					
t_{37} / t_{77}	0.5500 / 0.5000	40 / 40					
t_{38} / t_{78}	0.5250 / 0.4750	40 / 40					
t_{39} / t_{79}	0.5000 / 0.4500	40 / 40					
t_{40} / t_{80}	0.4750 / 0.4250	40 / 40					

Appendix B. The reduced Twolevel Power Market Model

B.1. Spot Market Level: Optimal Generation Investment and Spot Market Behavior.

$$\max \quad \sum_{\mathrm{s}\in \mathrm{S}} \pi_{\mathrm{s}} \sum_{n\in N} \sum_{t\in T} \tau \left(\int_0^{d_{t,n,\mathrm{s}}} p_{t,n,\mathrm{s}}(\xi)\,\mathrm{d}\xi + \sum_{g\in G_n^{\mathrm{priv}}} c_g^{\mathrm{var}} y_{t,g,\mathrm{s}}^{\mathrm{spot}} \right) - \sum_{n\in N} \sum_{g\in G_n^{\mathrm{priv}}} c_g^{\mathrm{inv}} \bar{y}_g$$

s.t. **Generation Capacity Limits (GCL):**

$$y_{t,g,\mathrm{s}}^{\mathrm{spot}} \le \alpha_g \tau \bar{y}_g \quad \text{for all } n \in N, g \in G_n^{\mathrm{priv}}, t \in T, \mathrm{s} \in \mathrm{S}$$

$$\bar{y}_g \le \bar{y}_g^{\mathrm{ub}} \quad \text{for all } n \in N, g \in G_n^{\mathrm{priv}}, t \in T, \mathrm{s} \in \mathrm{S}$$

Zonal Kirchhoff's First Law (ZKFL):

$$\sum_{n\in N\cap Z_k} d_{t,n,\mathrm{s}} = \sum_{n\in N\cap Z_k} \sum_{g\in G_n^{\mathrm{priv}}} y_{t,g,\mathrm{s}}^{\mathrm{spot}} + \sum_{l\in \delta_{Z_k}^{\mathrm{in}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{spot}} - \sum_{l\in \delta_{Z_k}^{\mathrm{out}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{spot}} \quad \text{for all } Z_k \in Z_{\mathrm{s}}, t \in T, \mathrm{s} \in \mathrm{S}$$

Market Coupling Flow Restrictions (MCF):

$$-\beta_l \bar{f}_l \le f_{t,l,\mathrm{s}}^{\mathrm{spot}} \le \beta_l \bar{f}_l \quad \text{for all } l \in L_{\mathrm{s}}^{\mathrm{inter}} \cap L^{\mathrm{ex}}, t \in T, \mathrm{s} \in \mathrm{S}$$

$$-z_l \beta_l \bar{f}_l \le f_{t,l,\mathrm{s}}^{\mathrm{spot}} \le z_l \beta_l \bar{f}_l \quad \text{for all } l \in L_{\mathrm{s}}^{\mathrm{inter}} \cap L^{\mathrm{new}}, t \in T, \mathrm{s} \in \mathrm{S}.$$

Variable Restrictions (VR):

$$y_{t,g,\mathrm{s}}^{\mathrm{spot}} \ge 0 \quad \text{for all } n \in N, g \in G_n^{\mathrm{priv}}, t \in T, \mathrm{s} \in \mathrm{S}$$

$$d_{t,n,\mathrm{s}} \ge 0 \quad \text{for all } n \in N, t \in T, \mathrm{s} \in \mathrm{S}$$

B.2. **Redispatch Level: Optimal Transmission Investment and Optimal Cost-based Redispatch.**

$$\max \quad \sum_{\mathrm{s}\in \mathrm{S}} \pi_{\mathrm{s}} \sum_{n\in N} \sum_{t\in T} \tau \left(\int_0^{d_{t,n,\mathrm{s}}} p_{t,n,\mathrm{s}}(\xi)\,\mathrm{d}\xi - \sum_{g\in G_n^{\mathrm{all}}} c_g^{\mathrm{var}} y_{t,g,\mathrm{s}}^{\mathrm{redi}} \right) - \sum_{l\in L^{\mathrm{new}}} c_l^{\mathrm{inv}} z_l - \sum_{n\in N} \sum_{g\in G_n^{\mathrm{all}}} c_g^{\mathrm{inv}} \bar{y}_g$$

s.t. **Kirchhoff's First Law (KFL):**

$$d_{t,n,\mathrm{s}} = \sum_{g\in G_n^{\mathrm{all}}} y_{t,g,\mathrm{s}}^{\mathrm{redi}} + \sum_{l\in \delta_n^{\mathrm{in}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{redi}} - \sum_{l\in \delta_n^{\mathrm{out}}(L)} f_{t,l,\mathrm{s}}^{\mathrm{redi}} \quad \text{for all } n\in N, t\in T, \mathrm{s}\in \mathrm{S}$$

Kirchhoff's Second Law (KSL):

$$f_{t,l,\mathrm{s}}^{\mathrm{redi}} - B_l(\theta_{t,n,\mathrm{s}} - \theta_{t,j,\mathrm{s}}) = 0 \quad \text{for all } l=(n,j)\in L^{\mathrm{ex}}, t\in T, \mathrm{s}\in \mathrm{S}$$

$$-M_l(1-z_l) \le f_{t,l,\mathrm{s}}^{\mathrm{redi}} - B_l(\theta_{t,n,\mathrm{s}} - \theta_{t,j,\mathrm{s}}) \le M_l(1-z_l) \quad \text{for all } l=(n,j)\in L^{\mathrm{new}}, t\in T, \mathrm{s}\in \mathrm{S}$$

Voltage Phase Angle of Reference Node (VPA):

$$\theta_{t,\hat{n},\mathrm{s}} = 0 \quad \text{for all } t\in T, \mathrm{s}\in \mathrm{S}$$

Transmission Flow Limits (TFL):

$$-\bar{f}_l \le f_{t,l,\mathrm{s}}^{\mathrm{redi}} \le \bar{f}_l \quad \text{for all } l\in L^{\mathrm{ex}}, t\in T, \mathrm{s}\in \mathrm{S}$$

$$-z_l\bar{f}_l \le f_{t,l,\mathrm{s}}^{\mathrm{redi}} \le z_l\bar{f}_l \quad \text{for all } l\in L^{\mathrm{new}}, t\in T, \mathrm{s}\in \mathrm{S}$$

Generation Capacity Limits (GCL):

$$y_{t,g,\mathrm{s}}^{\mathrm{redi}} \le \alpha_g \tau \bar{y}_g \quad \text{for all } n\in N, g\in G_n^{\mathrm{all}}, t\in T, \mathrm{s}\in \mathrm{S}$$

Variable Restrictions (VR):

$$y_{t,g,\mathrm{s}}^{\mathrm{redi}} \ge 0 \quad \text{for all } n\in N, g\in G_n^{\mathrm{all}}, t\in T, \mathrm{s}\in \mathrm{S}$$

$$z_l \in \{0,1\} \quad \text{for all } l\in L^{\mathrm{new}}$$

Appendix C. Notation and Symbols

Table 5. Sets

Symbol	Description
$\mathcal{G}$	Transmission network
N	Set of nodes of the transmission network
T	Set of time periods
S	Set of all considered scenarios
Z_{s}	Set of zones in scenario $\mathrm{s} \in \mathrm{S}$
G_n^{all}	Set of all generation technologies at node $n \in N$
G_n^{priv}	Set of private generation technologies at node $n \in N$
G_n^{bu}	Set of backup generators at node $n \in N$
L^{ex}	Set of all existing transmission lines (set of arcs of graph $\mathcal{G}$)
L^{new}	Set of all candidate transmission lines
$L_{\mathrm{s}}^{\mathrm{inter}}$	Set of all inter-zonal transmission lines in scenario $\mathrm{s} \in \mathrm{S}$

Table 6. Variables

Symbol	Description	Unit
$d_{t,n,\mathrm{s}}$	Demand of node $n \in N$ in time period t and scenario $\mathrm{s} \in \mathrm{S}$	MW
$p_{t,n,\mathrm{s}}$	Electricity price at node $n \in N$ in time period $t \in T$ and scenario $\mathrm{s} \in \mathrm{S}$	€/MWh
$\bar{y}_g$	Installed generation capacity of generator $g \in G_n^{\mathrm{all}}, n \in N$	MW
$y_{t,g,\mathrm{s}}$	Power generation of generator $g \in G_n^{\mathrm{all}}, n \in N$ in scenario $\mathrm{s} \in \mathrm{S}$	MW
$f_{t,l,\mathrm{s}}$	Power flow on line $l \in L^{\mathrm{ex}} \cup L^{\mathrm{new}}$ in time period t and $\mathrm{s} \in \mathrm{S}$	MW
$\theta_{t,n,\mathrm{s}}$	Voltage angle at node $n \in N$ in time period t and $\mathrm{s} \in \mathrm{S}$	rad
z_l	Decision variable for candidate line $l \in L^{\mathrm{new}}$	—

Table 7. Parameters

Symbol	Description	Unit
c_g^{inv}	Investment cost of candidate generation technology $g \in G_n^{\mathrm{all}}, n \in N$	€/MW
c_g^{var}	Variable cost of generation technology $g \in G_n^{\mathrm{all}}, n \in N$	€/MWh
c_l^{inv}	Investment cost of candidate transmission line $l \in L^{\mathrm{new}}$	€
B_l	DC power flow scaled susceptance of line $l \in L^{\mathrm{ex}} \cup L^{\mathrm{new}}$	MW
$\bar{f}_l$	Maximum power flow on line $l \in L^{\mathrm{ex}} \cup L^{\mathrm{new}}$	MW
M_l	Parameter for linearization of Kirchhoff's second law for line $l \in L$	—
τ	Length between two consecutive time periods $t, t+1 \in T$	h
α_g	Equivalent availability parameter of generator $g \in G_n^{\mathrm{all}}, n \in N$	—
π_{s}	Probability of scenario $\mathrm{s} \in \mathrm{S}$	—