The Impact of Neighboring Markets on Renewable Locations, Transmission Expansion, and Generation Investment

Jonas Egerer, Veronika Grimm, Thomas Kleinert, Martin Schmidt, and Gregor Zöttl

Abstract. Many long-term investment planning models for liberalized electricity markets either optimize for the entire electricity system or focus on confined jurisdictions, abstracting from adjacent markets. In this paper, we provide models for analyzing the impact of the interdependencies between a core electricity market and its neighboring markets on key long-run decisions. This we do both for zonal and nodal pricing schemes. The identification of welfare optimal investments in transmission lines and renewable capacity within a core electricity market requires a spatially restricted objective function, which also accounts for benefits from cross-border electricity trading. This leads to mixed-integer nonlinear multilevel optimization problems with bilinear nonconvexities for which we adapt a Benders-like decomposition approach from the literature. In a case study, we use a stylized six-node network to disentangle different effects of optimal regional (as compared to supra-regional) investment planning. Regional planning alters investment in transmission and renewable capacity in the core region, which affects private investment in generation capacity also in adjacent regions and increases welfare in the core region at the cost of system welfare. Depending on the congestion-pricing scheme, the regulator of the core region follows different strategies to increase welfare causing distributional effects among stakeholders.

Key words: OR in energy, Neighboring Markets, Renewable and Network Expansion, Multilevel Optimization, Benders Decomposition.

1. Introduction

In recent years, various academic papers have focused on modeling long-run decisions on transmission and generation expansion in liberalized electricity markets; see, e.g., Grimm, Martin, et al. (2016), Kleinert and Schmidt (2019), Munoz et al. (2016), Pozo et al. (2013), and Sauma and Oren (2009), to name only a few. The fact that in today's electricity markets various agents take decisions under different objectives gives rise to methodological challenges in the context of multilevel mixed-integer nonlinear optimization models, which form a very hard class of optimization problems. Typical models focus on a specific market region, abstracting from the fact that various regional electricity markets often are interconnected and, thus, a regional market's outcome is influenced by decisions in neighboring markets and vice versa. Issues arising in the context of adjacent jurisdictions that potentially have opposing goals play an increasingly important role in the regulation of electricity markets. This is prominently reflected by the ongoing and intense policy debates in this context. In these debates, the resulting interaction and coordination issues between different regional markets often are referred to as "seams-issues". For prominent policy discussions on those seams-issues for Europe, see, e.g., European Commission et al. (2014), Glachant and Meeus (2018), Newbery et al. (2018),

Date: October 30, 2020.
2010 *Mathematics Subject Classification.* 90C90, 90C30, 90C11, 91B26, 91A65.

and Roques and Verhaeghe (2016). Moreover, the most recent advances of the European Commission regarding the precise design of European electricity markets heavily put a focus on the potentially arising problems, which obtain at the borders of different jurisdictions; see, e.g., BMWi (2020) and European Parliament and European Commission (2019). For the ongoing discussion regarding seems issues in the US see, e.g., Dennis et al. (2016), NREL (2018), and NRRI (2015).

Two examples where regional and system-wide perspectives differ are the regional distribution of costs and benefits of transmission projects as well as regional targets and support schemes versus system-wide approaches to foster investment in low-carbon technologies. As an example, in the European electricity system, in which most costs for transmission investment and renewable support schemes are covered by national charges on electricity demand, national network planning tends to invest too much in the enforcement of the grid within the country to promote the integration of renewable electricity generation at the national level. Electricity market models (like the one presented in this paper) that incorporate the perspective of individual regions can provide valuable insights in this context by evaluating the effects of conflicting regional decisions and the inflicted inefficiency at system level.

In this paper, we extend the literature on multilevel electricity market modeling by a rigorous consideration of regional objectives in a framework of coupled regional markets with cross-border interdependencies. We build on a multilevel approach that models transmission expansion decided proactively by a regulator, followed by generation investment and market operation decided on by private firms (see, e.g., Sauma and Oren (2006) for nodal pricing), as well as redispatch operations in case of zonal pricing decided on by the network operator. The articles that we build on are Grimm, Martin, et al. (2016), where we considered transmission and generation expansion for a given zonal configuration, on Grimm, Kleinert, et al. (2019), where we abstracted from transmission expansion but considered endogenous zonal configurations, as well as Kleinert and Schmidt (2019), where we combined transmission and generation expansion with endogenous zonal configurations. We expand the model of the latter article by introducing adjacent market regions that have interconnected electricity markets. Conventional generation investment and spot-market trading remains in line with the previous papers. Market participants invest in conventional generation capacity in all regional electricity markets in anticipation of market prices evolving at the inter-regionally coupled spot markets. In our framework, we assume that a local regulatory authority, which we simply call the regulator, is only responsible for a part of the inter-regional electricity market, which we refer to as the core electricity market. The regulator decides on transmission projects, capacity of renewable energy sources (RES), and backup capacity with the objective to maximize the welfare of the respective core region. This approach reflects that these decisions are in many markets not only relying on markets but that they are predetermined by regional planning processes, e.g., for the transmission network, due to regional objectives on renewable deployment, or due to regional regulations on security of supply.

The proper consideration of regional objectives in our setup inevitably requires the precise consideration of cross-border trade in coupled electricity markets. This results in nonconvex bilinearities in the first-level objective function, however. These nonconvexities have not been part of the models discussed in the above mentioned papers and render the problem significantly more challenging. Fortunately, we show that it is possible to mathematically exploit the problem-specific structure of the model so that a reformulation is available that can be solved to global optimality with a similar Benders-like decomposition approach as it has been developed and used in Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019). The

focus of this paper thus is not on a novel algorithmic technique for solving the considered models. Rather, we provide a way to accurately include revenues from cross-border trade into the first-level objective function in a way that allows to exploit available techniques for solving the multilevel problem. Our approach allows to study interesting and topical economic questions that cannot be answered using the models in the existing literature.

To illustrate the impact of the consideration of neighboring markets on the economic outcome, we apply our solution approach to a test instance comprising of a core market region and two adjacent market regions with distinct characteristics. In four different scenarios, three with different bidding zone configurations and one with nodal pricing, we cover a large variety of congestion-pricing schemes in the core region. In our analysis, we compare two different setups: One in which the regulator has a supra-regional objective versus the case that the regulator only focuses on the core region. We then determine the impact on investment in transmission capacity as well as location and technology choice for RES and, as a consequence, also changed incentives for private investment in conventional generation. Our main findings are the following: First, increased regional welfare resulting from a purely regional planning perspective induces disproportionally large welfare losses in some neighboring markets. However, in some cases, selected adjacent market regions even co-benefit. Second, also the distribution of economic rents within the core region is affected considerably. In particular, the distribution of consumer surplus as well as investment costs and rents of RES and the transmission network deviates substantially across multiple bidding zones or nodes in the core region for different objectives of the regulator. That is, some zones within the core region do not benefit and even loose in case of the regional planning perspective. We find that those effects occur due to price differences between the two considered scenarios (supra-regionally versus regionally oriented regulator) in a limited number of hours.

Our work contributes to several strands of literature. In the following, we review the related strands of literature in detail and, for each strand, we emphasize our particular contribution. We expand models on transmission planning with anticipation of generation investment by the consideration of a regulator that takes care only for a part of the considered network area when investing in transmission capacity, RES, and backup capacity. For the case of nodal pricing, we refer to the early contribution by Sauma and Oren (2006) as well as to the more recent work by Pozo et al. (2013). While under the typical assumptions, in particular the assumption of competitive firms, the nodal pricing outcome coincides with the welfare optimum, this is not the case if the regulator takes care only for a part of the network but firms act on inter-regional markets. This also affects the complexity of modeling of the respective situation, i.e., multilevel models are required. For further contributions in the context of nodal pricing; see, e.g., Egerer and Schill (2014), who analyze transmission and generation investment for different scenarios of pricing RES curtailment in a case study. Mínguez and García-Bertrand (2016) analyze the case of robust optimization when choosing network expansion. Furthermore, Bravo et al. (2016) consider the impact of different network payment schemes on optimal investment decisions. Several other articles also consider optimal investment and placement of RES capacity; see e.g., O'Neill et al. (2013) or Spyrou et al. (2017).

In case of zonal pricing, long-run investment incentives of private companies are not aligned with the overall system optimum due to distorted zonal price signals at the spot market; cf. Holmberg and Lazarczyk (2015). An adequate model of a zonal-pricing electricity system thus requires a multilevel approach to accurately represent the diverging incentives of the regulator and private firms as introduced and analyzed in Grimm, Martin, et al. (2016). Based on this framework, Grimm,

Kleinert, et al. (2019) and Kleinert and Schmidt (2019) as well as Ambrosius, Grimm, et al. (2018) determine the system-optimal price zones anticipating firms' investment and production decisions. Ambrosius, Egerer, et al. (2019) focus on the impact of uncertainty about the future zonal configuration on transmission and generation investment. Our approach extends those models by providing tools to rigorously analyze cross-border trade for a purely regional objective of the regulator in a core region.

While the literature referred to above considers a regulator who adopts a system-optimal perspective, another strand of literature deals with decisions by governments or regulators based on a purely regional perspective. For example, Buijs and Belmans (2012), Huppmann and Egerer (2015), and Tohidi, Hesamzadeh, and Regairaz (2018) consider network expansion decided on by different regional governments prior to nodal pricing. Kasina and Hobbs (2020) evaluate the value of cooperation for each region in a similar setting and allow for private investment in generation capacity. The perspective of purely regional planners is also considered by Tohidi and Hesamzadeh (2014) and Tohidi, Hesamzadeh, and Regairaz (2018) under the assumption that the planners aim at minimizing resource costs. Our work adds to those contributions by additionally taking into account governmental decisions regarding RES investment and placement. Moreover, to the best of our knowledge, our contribution is the first one to consider such a purely regional perspective of governmental decisions in a context of zonal pricing with redispatch after spot-market trading. A detailed representation of inter-regional power flows in our approach also accounts for revenues from cross-border trade and thus requires to model market prices as primal variables. This gives rise to nonconvex bilinear terms in the upper level of our multilevel problem.

The remainder of this paper is organized as follows. In Sections 2 and 3, we state a zonal and a nodal pricing model. Section 4 describes the solution approach and Section 5 introduces a six-node example, for which we provide results in Section 6. Finally, Section 7 discusses the main results and concludes.

2. The Mixed-Integer Multilevel Market Model

In our model, we consider an electricity market that is surrounded by other market areas. We call the considered market area the core region and assume that it is governed by a local (e.g., national) regulatory authority, which we simply call the regulator. As in many liberalized electricity markets, some decisions are taken (or governed) by the regulator, while other decisions are taken by private firms. In particular, we assume that the regulator maximizes welfare with a focus on the core region and, within the core region, decides on the expansion of network capacity, on the technology and placement of RES to reach a regional renewable target, and on investment in backup capacities. This takes into account that, in many markets, the expansion of renewable energies and backup capacities is planned centrally and is only realized afterward by private companies, e.g., through tenders. For network and RES investment in neighboring market areas, the core region regulator assumes a predetermined scenario. Private firms decide on the expansion of conventional generation capacity and electricity production. In doing so, they do not solely focus on the core region, but on price signals at all interconnected regional markets. Our model can thus make visible to what extent the objective function of the regulator, who focuses only on the core region, affects the decisions of private firms as well as aggregated welfare and disaggregated welfare for individual market areas.

A mathematical model of this setup leads to a mixed-integer nonlinear trilevel market model. In the following, we present every level of this model in detail. Our approach builds on previous work on multilevel electricity market modeling,

in particular on Grimm, Kleinert, et al. (2019) as well as Kleinert and Schmidt (2019), and extends this setup by the consideration of multiple market areas and RES investment. For doing so, we supplement the modeling approach with a more complex modeling of the first level, which allows to focus on the decisions on a subset of the regions, taking into account the prices at the borders. Moreover, we integrate a larger number of different decisions, e.g., the decisions on network expansion, RES locations, and backup capacity.

For a better understanding of the overall model, we first give a brief overview of each level and the interdependencies between the levels; see Figure 1. On the

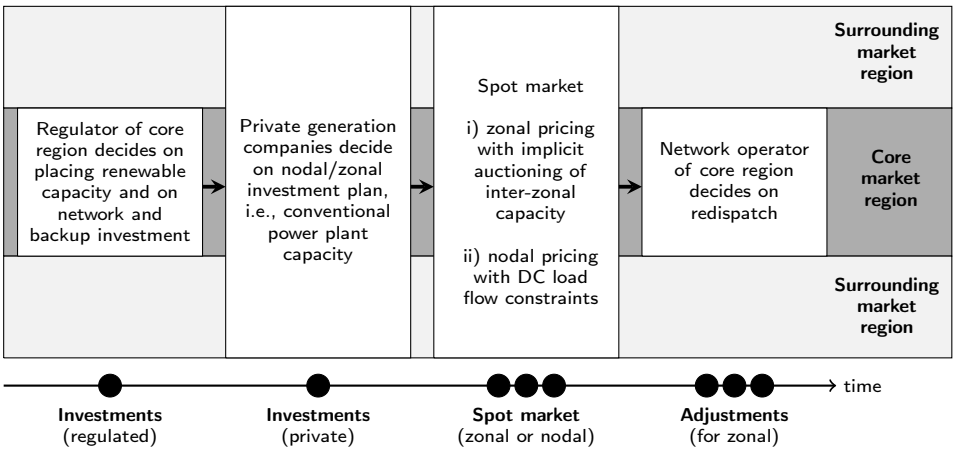

FIGURE 1. Timeline of regional decisions in the core market region and market operation in the entire market region. Single dots represent decisions taken once, whereas three dots represent decisions taken in multiple time periods.

first level, the regulator of the core region decides on network expansion, investment as well as placement of RES, and investment in backup generators. We do not specify ownership for transmission lines as well as for RES and backup capacity but assume that the regulator delegates operation of the transmission system and of backup capacity to a benevolent network operator. We further assume that generation from RES capacity is offered at the spot market at marginal cost but we do not specify ownership of RES investment. This reflects the common practice to establish mechanisms, e.g., tenders, that ensure a certain renewable capacity expansion, where this capacity is later on made available at negligible marginal cost, or even dispatched with priority. The goal of the regulator is to maximize the welfare within the core region, which combines regional consumer, producer, and network rents, as well as trade payments and parts of the network rents at the border to neighboring market areas. To this end, the regulator anticipates the decisions of the market participants of all regions. Thus, the anticipation of quantities that are decided on by the agents on the two lower levels also influences the decisions of the regulator.

The second level models long-term conventional generation investment decisions of private firms and multiple periods of electricity market trading. Here, consumers and generating firms act on the electricity market as to maximize their individual profits. We assume market outcomes with perfectly competitive behavior, which result from a power exchange or an independent system operator clearing the entire spot market with supply and demand bids from market players in all market areas and trade constraints for either nodal or zonal pricing. In contrast to the first

level, the second level considers decision making in all market areas. Clearly, the individual decisions of the agents of the second level are subject to the regulatory setting and first-level decisions, i.e., network expansion and renewable placement decisions as specified on the first level.

Finally, on the third level, the network operator maximizes welfare and adjusts spot-market outcomes to enable feasible technical operation of the electricity network. In this paper, we consider a cost-based redispatch as it is used in Austria, Switzerland, or Germany. Thus, in case of infeasibilities, the network operator redispatches production quantities within the core region at minimum cost. To this end, the network operator may use backup generation capacities that are commissioned by the regulator, i.e., decided upon in the first level. Under the assumption of a cost-based redispatch, third-level decisions do not affect bids into the spot market at the second level as generation companies do not make additional profits from redispatch of production quantities. If generation redispatch and backup generation do not suffice to establish a feasible power flow, the network operator, as a measure of last resort, may as well decide to not supply all traded demand within its own market region, which is called load shedding. Obviously, the technical feasibility of traded quantities depends on the first-level decisions of the regulator.

In the remainder of this section, we first give a detailed overview of the mathematical notation before we specify every level of the trilevel model in detail.

2.1. **Notation and Mathematical Setup.** We now start by describing the general notation we use, which is based on both Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019). All sets, parameters, and variables that are used in the remainder of this section are summarized in Appendix A. We consider an electricity transmission network $\mathcal{G} = (N, L)$ with a set of nodes N and a set of directed transmission lines $L \subseteq N \times N$. Throughout the paper, we make use of the standard δ-notation, i.e., the sets of in- and outgoing lines of a node set $N' \subseteq N$ are denoted by $\delta^{\text{in}}_{N'}$ and $\delta^{\text{out}}_{N'}$, respectively. More formally, we have

$$\delta^{\text{in}}_{N'} := \{l \in L \colon l = (n, m) \text{ with } n \notin N', m \in N'\},$$
$$\delta^{\text{out}}_{N'} := \{l \in L \colon l = (n, m) \text{ with } n \in N', m \notin N'\}.$$

We distinguish between a core region $N^{\text{core}} \subseteq N$ and surrounding markets $N^{\text{sur}} \subseteq N$ with $N^{\text{core}} \cap N^{\text{sur}} = \emptyset$ and $N^{\text{core}} \cup N^{\text{sur}} = N$. The core market is composed out of k pre-specified connected bidding zones that are denoted as parts of a partition $Z_1 \cup \cdots \cup Z_k = N^{\text{core}}$ with $1 \leq k \leq |N^{\text{core}}|$. The surrounding markets form bidding zones as well, i.e., $Z_{k+1} \cup \cdots \cup Z_p = N^{\text{sur}}$ with $1 \leq p - k \leq |N^{\text{sur}}|$. For all transmission lines $l \in L$ we denote their susceptance by B_l. Moreover, we distinguish between existing lines L^{ex} with given capacity $\bar{f}_l > 0$ and candidate lines L^{new} that can be built in the course of network expansion. Hence, $L = L^{\text{ex}} \cup L^{\text{new}}$ holds. The capacity and investment costs of an expansion module are given by $\bar{f}^{\text{mod}}_l$ and c^{mod}_l, $l \in L^{\text{new}}$. We further specify inter-zonal transmission lines

$$L^{\text{inter}} := \{l = (n, m) \in L \colon \exists i, j \in [p] \text{ with } n \in Z_i, m \in Z_j \text{ and } i \neq j\}$$

and transmission lines

$$L^{\text{core}} := \{l = (n, m) \in L \text{ with } n, m \in N^{\text{core}}\}$$

within the core region. Without loss of generality, we assume that inter-zonal lines between the core market and the surrounding markets are always directed towards the surrounding markets, i.e.,

$$\{l = (n, m) \text{ with } n \in N^{\text{sur}}, m \in N^{\text{core}}\} = \emptyset$$

holds. Note that we further assume $L^{\text{new}} \subseteq L^{\text{core}}$, since network expansion is only decided within the core market in our model.

At every node $n \in N$, we consider an aggregated demand of the consumers at that node. We further introduce a given set of time periods $T = \{1, \dots, |T|\}$, where $|T|$ is the number of time periods. Every time period $t \in T$ has a length τ_t. Note that in our setting, we have no dependencies between the time periods. Thus, our setting is also capable of modeling stochasticity if this stochasticity is captured using multiple scenarios. The "length" τ_t then corresponds to the probability of the corresponding scenario t. Elastic demand at node $n \in N$ in time period $t \in T$ is modeled by an inverse demand function $p_{n,t}(d_{n,t})$, where $d_{n,t}$ denotes the consumer's demand. Here, we make the two following assumptions.

Assumption 1. *All inverse demand functions $p_{n,t}$ are linear and strictly decreasing, i.e., $p_{n,t}(d_{n,t}) = a_{n,t} + b_{n,t} d_{n,t}$ with $a_{n,t} > 0$ and $b_{n,t} < 0$.*

As a consequence of the inverse demand functions being strictly decreasing, gross consumer surplus

$$\tau_t \int_0^{d_{n,t}} p_{n,t}(\omega)\, \mathrm{d}\omega$$

is a strictly concave function.

Assumption 2. *All demands are strictly positive, i.e., $d_{n,t} > 0$ holds for all $n \in N$ and all $t \in T$.*

Since we consider an aggregated demand at every node, this is a reasonable assumption. Both the assumption of linear demand functions as well as of strictly positive demands are needed to model spot-market prices in the primal constraints of the second-level problem; see Section 2.3.

For a given network node $n \in N$, G_n^{all} denotes a finite set of existing and candidate generation technologies. We use the set G_n^{ex} for already existing generation technologies and the set G_n^{new} for candidate generation technologies, i.e., $G_n^{\text{all}} = G_n^{\text{new}} \cup G_n^{\text{ex}}$ holds. We further distinguish between conventional generators $g \in G_n^{\text{conv}}$, renewable generators $g \in G_n^{\text{res}}$, and backup generators $g \in G_n^{\text{bu}}$. Hence, $G_n^{\text{all}} = G_n^{\text{conv}} \cup G_n^{\text{res}} \cup G_n^{\text{bu}}$ holds as well. For all existing generators $g \in G_n^{\text{ex}}$, the capacity is fixed and given by $\bar{q}_g^{\text{fix}}$. In contrast, private firms can invest in generation capacity $\bar{q}_g$ of candidate conventional generators $g \in G_n^{\text{new}} \cap G_n^{\text{conv}}$. The regulator of the core region decides on the placement, i.e., the node $n \in N$, of modules of renewable generation projects $g \in G_n^{\text{new}} \cap G_n^{\text{res}}$ with a given module capacity $\bar{q}_g^{\text{mod}}$. New investment in renewable generation outside the core region is not considered, i.e., $G_n^{\text{new}} \cap G_n^{\text{res}} = \emptyset$ holds for all $n \in N^{\text{sur}}$. The amount of renewable generation capacity outside the core region is considered by the regulator of the core region as an exogenous parameter. Furthermore, the regulator of the core region can invest in conventional capacities $\bar{q}_g$ of backup generators $g \in G_n^{\text{bu}}, n \in N^{\text{core}}$. We assume $G_n^{\text{bu}} \cap G_n^{\text{ex}} = \emptyset$ for all $n \in N^{\text{core}}$, i.e., there are no backup generators yet. Let us also briefly sketch the cost structure of generators. All candidate generators $g \in G_n^{\text{new}}$ have investment costs $c_g^{\text{inv}} \geq 0$ per installed MW. Variable costs of production $q_{g,t}$ of generator $g \in G_n^{\text{all}}, n \in N$, are denoted by $c_g^{\text{var}} \geq 0$. These costs are zero for all renewable generators $g \in G_n^{\text{res}}$. Finally, for every generator $g \in G_n^{\text{all}}$ the actual available capacity varies over time (due to weather conditions, maintenance work, etc.) and is determined by capacity factors $\omega_{g,t} \in [0, 1]$.

2.2. **First-Level Problem: Network Expansion, Renewable Investment, and Backup Generation Investment within the Core Market.** The first-level problem models the regulator overseeing her market area, i.e., the core region, which is embedded in a larger inter-connected electricity market. Inside the core region, the regulator decides on network expansion, on investment in renewable generation projects, and on investment in backup generation capacities. The latter

capacities can be used to prevent excessive reallocation of spot-market quantities during redispatch; cf. Section 2.4. The goal at this level is to maximize welfare within the core region. Network expansion within the core region is modeled by integer variables

$$y_l \in \{0, \dots, \bar{y}_l\} \subseteq \mathbb{N}_0 \quad \text{for all } l \in L^{\text{new}}, \tag{1}$$

indicating how often a module is built for line l. The maximum number of modules that can be invested in is $\bar{y}_l$. Similarly, investment in renewable generation projects is modeled by integer variables

$$x_g \in \{0, \dots, \bar{x}_g\} \subseteq \mathbb{N}_0 \quad \text{for all } g \in G_n^{\text{res}},\ n \in N^{\text{core}}, \tag{2}$$

that specify how many modules are built per project. For each renewable generation project $g \in G_n^{\text{new}}, n \in N^{\text{core}}$, the available capacity is then given by $\bar{q}_g^{\text{mod}} x_g$. Note that this is in contrast to conventional and backup generation capacity that we model using continuous variables. However, the integrality of the decisions on renewable generation capacity is needed for the computational tractability of the model. To the best of our knowledge, no effective solution techniques exist for the situation in which linking variables are not discrete. This is discussed in more detail in Section 4, where we propose the solution approach.

Following the practice of regional renewable targets (e.g., national targets for European countries in 2020) we set such a target for the core region. As investment in renewable capacity is discrete, we do this by defining a corridor with an upper bound s (i.e., the aspired political renewable target) and a lower bound r (i.e., the minimal required realization). These bounds refer to a share of annual available renewable generation of expected annual demand in the core region, i.e., we impose the constraints

$$\begin{aligned}
\sum_{t\in T}\left(\sum_{n\in N^{\text{core}}}\sum_{g\in G_n^{\text{res}}\cap G_n^{\text{ex}}}\tau_t\bar{q}_g^{\text{fix}} + \sum_{g\in G_n^{\text{res}}\cap G_n^{\text{new}}}\tau_t\bar{q}_g^{\text{mod}}x_g\right) &\geq r\sum_{t\in T}\sum_{n\in N^{\text{core}}}\tau_t d_{n,t}^{\text{ref}},\\
\sum_{t\in T}\left(\sum_{n\in N^{\text{core}}}\sum_{g\in G_n^{\text{res}}\cap G_n^{\text{ex}}}\tau_t\bar{q}_g^{\text{fix}} + \sum_{g\in G_n^{\text{res}}\cap G_n^{\text{new}}}\tau_t\bar{q}_g^{\text{mod}}x_g\right) &\leq s\sum_{t\in T}\sum_{n\in N^{\text{core}}}\tau_t d_{n,t}^{\text{ref}},
\end{aligned} \tag{3}$$

with $0 \leq r \leq s \leq 1$.

Finally, the regulator can invest in capacities $\bar{q}_g$ of candidate backup generators $g \in G_n^{\text{bu}}$ located at core nodes $n \in N^{\text{core}}$, i.e.,

$$0 \leq \bar{q}_g \leq \bar{q}_g^{\max} \quad \text{for all } g \in G_n^{\text{bu}},\ n \in N^{\text{core}}, \tag{4}$$

where $\bar{q}_g^{\max}$ specifies the maximum backup capacity that can be installed.

Next, we derive the objective function of the first level. Regional welfare is given as gross consumer surplus less generation costs after redispatch, investment costs for conventional, renewable, and backup generators, as well as for network expansion. The gross consumer surplus and generation costs involve demand and generation quantities after redispatch $d_{n,t}^{\text{red}}$ and $q_{g,t}^{\text{red}}$, which are formally introduced in Section 2.4. Remember that investment in transmission lines outside the core region as well as investment in renewables in neighboring markets is not decided on by the regulator of the core region. Further, one has to take into account load shedding costs $c^{\text{ls}} d_{n,t}^{\text{ls}}$, which represent a price ceiling corresponding to the value of lost load; cf. Section 2.4. Finally, congestion rents and payments for import and export on links with neighboring markets (partly) add to regional welfare. These payments depend on genuine second-level variables for the spot-market price $\pi_{n,t}$ and the power flow $f_{l,t}^{\text{spot}}$; see the second-level model in Section 2.3. The congestion rent on transmission line $l = (n, m)$ is given by $(\pi_{m,t} - \pi_{n,t}) f_{l,t}^{\text{spot}}$, which may be split up between the network operators at nodes n and m according to shares $0 \leq s_n^{\text{cong}} \leq 1$

and $0 \leq s_m^{\text{cong}} = 1 - s_n^{\text{cong}}$. Thus, the network operator at node n receives the congestion rent

$$s_n^{\text{cong}} \left(\pi_{m,t} - \pi_{n,t}\right) f_{l,t}^{\text{spot}}.$$

Together with payments for import and export $\pi_{n,t} f_{l,t}^{\text{spot}}$, trans-regional payments at node n are given by the nonconvex function

$$\begin{aligned} s_n^{\text{cong}}(\pi_{m,t} - \pi_{n,t}) f_{l,t}^{\text{spot}} + \pi_{n,t} f_{l,t}^{\text{spot}} &= s_n^{\text{cong}} \pi_{m,t} f_{l,t}^{\text{spot}} + (1 - s_n^{\text{cong}}) \pi_{n,t} f_{l,t}^{\text{spot}} \\ &= \left(s_n^{\text{cong}} \pi_{m,t} + s_m^{\text{cong}} \pi_{n,t}\right) f_{l,t}^{\text{spot}}. \end{aligned}$$

Welfare of the core market is thus given by

$$\begin{aligned} \psi_1 := & \sum_{t \in T} \sum_{n \in N^{\text{core}}} \tau_t \left(\int_0^{d_{n,t}^{\text{red}}} p_{n,t}(\omega) \, \mathrm{d}\omega - \sum_{g \in G_n^{\text{all}}} c_g^{\text{var}} q_{g,t}^{\text{red}} \right) - \sum_{l \in L^{\text{new}}} c_l^{\text{mod}} y_l \\ & - \sum_{n \in N^{\text{core}}} \left(\sum_{g \in G_n^{\text{res}} \cap G_n^{\text{new}}} c_g^{\text{inv}} \bar{q}_g^{\text{mod}} x_g + \sum_{g \in G_n^{\text{conv}} \cap G_n^{\text{new}}} c_g^{\text{inv}} \bar{q}_g + \sum_{g \in G_n^{\text{bu}}} c_g^{\text{inv}} \bar{q}_g \right) \\ & - \sum_{t \in T} \sum_{n \in N^{\text{core}}} \tau_t c^{\text{ls}} d_{n,t}^{\text{ls}} \\ & + \sum_{t \in T} \sum_{l=(n,m) \in \delta_{N^{\text{core}}}^{\text{out}}} \tau_t \left(s_n^{\text{cong}} \pi_{m,t} + s_m^{\text{cong}} \pi_{n,t}\right) f_{l,t}^{\text{spot}}. \end{aligned} \tag{5}$$

Hence, the first-level problem reads

$$\max \quad \psi_1 \quad \text{s.t.} \quad (1)\text{–}(4). \tag{6}$$

This is a mixed-integer optimization problem with linear constraints and a nonlinear objective. The nonlinearities stem from the concave-quadratic gross consumer surplus terms and the terms modeling congestion rents and trans-regional payments. The latter terms are products of continuous second-level variables for the price $\pi_{n,t}$ and the power flow $f_{l,t}^{\text{spot}}$ and thus are nonconvex bilinear terms. Consequently, the modeling of congestion rents and trans-regional payments, that is required by considering multiple connected market areas, adds significant difficulty to the first level compared to what has been studied in Grimm, Kleinert, et al. (2019) or Kleinert and Schmidt (2019).

2.3. **Second-Level Problem: Conventional Generation Investment and Spot-Market Behavior.** At the second level, we model long-term conventional generation capacity investment and multiple periods of day-ahead spot-market trading. Consumers and generating firms want to maximize their individual profits. This results in various optimization problems, whose optimality conditions—together with suitably chosen market-clearing conditions—can be stacked to obtain a mixed complementarity problem. It is well known that, under the assumption of perfect competition, this mixed complementarity problem is equivalent to a welfare maximization problem; see, e.g., Grimm, Schewe, et al. (2017), where this is shown for a related model setup. We are aware of the fact that the assumption of perfect competition does not exactly reflect the situation of power markets. However, this is a common assumption in the electricity market modeling literature; cf., e.g., Boucher and Smeers (2001), Daxhelet and Smeers (2007), and Grimm, Martin, et al. (2016). In our multilevel context, this assumption is required both for computational reasons and also allows for a clear-cut analysis due to uniqueness of the resulting lower-level equilibria. For a study of multiplicity of equilibria in other related settings, see,

e.g., Krebs et al. (2018) and Zöttl (2010).In our case, the assumption of perfect competition yields the objective function

$$\psi_2 := \sum_{t\in T}\sum_{n\in N}\tau_t\left(\int_0^{d^{\text{spot}}_{n,t}} p_{n,t}(\omega)\,\mathrm{d}\omega - \sum_{g\in G^{\text{conv}}_n} c^{\text{var}}_g q^{\text{spot}}_{g,t}\right) - \sum_{n\in N}\sum_{g\in G^{\text{new}}_n\cap G^{\text{conv}}_n} c^{\text{inv}}_g \bar{q}_g. \tag{7}$$

Demand quantities are restricted by simple lower bounds

$$0 \le d^{\text{spot}}_{n,t} \quad \text{for all } n\in N,\ t\in T, \tag{8}$$

whereas generation quantities are also bounded above by capacities, i.e.,

$$0 \le q^{\text{spot}}_{g,t} \le \omega_{g,t}\bar{q}^{\text{fix}}_g \qquad \text{for all } g\in G^{\text{ex}}_n,\ n\in N,\ t\in T, \tag{9a}$$

$$0 \le q^{\text{spot}}_{g,t} \le \omega_{g,t}\bar{q}_g \qquad \text{for all } g\in G^{\text{new}}_n\cap G^{\text{conv}}_n,\ n\in N,\ t\in T, \tag{9b}$$

$$\bar{q}_g \le \bar{q}^{\max}_g \qquad \text{for all } g\in G^{\text{new}}_n\cap G^{\text{conv}}_n,\ n\in N, \tag{9c}$$

$$0 \le q^{\text{spot}}_{g,t} \le \omega_{g,t}\bar{q}^{\text{mod}}_g x_g \qquad \text{for all } g\in G^{\text{new}}_n\cap G^{\text{res}}_n,\ n\in N,\ t\in T. \tag{9d}$$

Note that x_g is a first-level integer variable, whereas $\bar{q}_g$ is a continuous second-level variable.

In zonal markets, spot-market flow on intra-zonal lines is unconstrained. In contrast, one needs to take into account capacities of existing and candidate inter-zonal transmission lines. This can be modeled by

$$-\beta_l\bar{f}_l \le f^{\text{spot}}_{l,t} \le \beta_l\bar{f}_l \qquad \text{for all } l\in L^{\text{ex}}\cap L^{\text{inter}},\ t\in T, \tag{10a}$$

$$-\beta_l\bar{f}^{\text{mod}}_l y_l \le f^{\text{spot}}_{l,t} \le \beta_l\bar{f}^{\text{mod}}_l y_l \qquad \text{for all } l\in L^{\text{new}}\cap L^{\text{inter}},\ t\in T, \tag{10b}$$

where $\beta_l\in[0,1]$ are exogenously given inter-zonal transmission capacity factors and $\bar{f}_l$ is the thermal capacity of line l. Furthermore, y_l is the first-level network expansion variable.

Finally, we impose zonal market-clearing conditions that state that the zonal demand and outflow equal the zonal generation and inflow for every zone and time period:

$$D_{i,t} = \sum_{n\in Z_i} d^{\text{spot}}_{n,t}, \qquad \text{for all } i\in[p],\ t\in T, \tag{11a}$$

$$Q_{i,t} = \sum_{n\in Z_i}\sum_{g\in G^{\text{all}}_n\setminus G^{\text{bu}}_n} q^{\text{spot}}_{g,t} \qquad \text{for all } i\in[p],\ t\in T, \tag{11b}$$

$$F^{\text{in}}_{i,t} = \sum_{l=(n,m)\in L^{\text{inter}},m\in Z_i} f^{\text{spot}}_{l,t} \qquad \text{for all } i\in[p],\ t\in T, \tag{11c}$$

$$F^{\text{out}}_{i,t} = \sum_{l=(n,m)\in L^{\text{inter}},n\in Z_i} f^{\text{spot}}_{l,t} \qquad \text{for all } i\in[p],\ t\in T, \tag{11d}$$

$$D_{i,t} + F^{\text{out}}_{i,t} = Q_{i,t} + F^{\text{in}}_{i,t} \qquad \text{for all } i\in[p],\ t\in T. \tag{11e}$$

For every $i\in[p]$ and $t\in T$, the dual variable of the last constraint corresponds to the resulting market price in zone i and time period $t\in T$; see Kleinert and Schmidt (2019). For strictly positive demands, see Assumption 2, these prices can be expressed in a primal formulation using the inverse demand functions $p_{n,t}$. Using Assumption 1, we can denote market prices $\pi_{n,t}$ by the linear constraints

$$\pi_{n,t} = a_{n,t} + b_{n,t}d^{\text{spot}}_{n,t} \quad \text{for all } n\in N,\ t\in T. \tag{12}$$

These prices occur in the objective function (5) of the first level for modeling trans-regional payments.

In total, the second-level problem reads

$$\max \quad \psi_2 \quad \text{s.t.} \quad (8)\text{–}(12), \tag{13}$$

which is a maximization problem with a concave-quadratic objective function over constraints that are parameterized by the first-level decisions and that are linear in the second-level variables.

2.4. **Third-Level Problem: Cost-Optimal Redispatch.** At the third level, the network operator resolves possible technical infeasibilities of spot-market results, i.e., he decides on cost-based redispatch, generation quantities of backup generators, as well as load shedding. When resolving infeasibilities within the borders of the core region, all flows $f^{\text{red}}_{l,t}$ of lines connecting the core region with surrounding regions are fixed to their spot-market values, i.e.,

$$f^{\text{spot}}_{l,t} = f^{\text{red}}_{l,t} \quad \text{for all } l \in \delta^{\text{out}}_{N^{\text{core}}},\ t \in T. \tag{14}$$

Load shedding is only applied if generation redispatch and backup generation are not sufficient to resolve infeasibilities. This can be modeled by imposing sufficiently large costs for load shedding, which refer to the value of lost load. We denote demand quantities after redispatch with $d^{\text{red}}_{n,t}$ and load shedding with $d^{\text{ls}}_{n,t} \geq 0$, respectively. These variables are connected in the following way:

$$d^{\text{red}}_{n,t} = d^{\text{spot}}_{n,t} - d^{\text{ls}}_{n,t} \quad \text{for all } t \in T,\ n \in N^{\text{core}},\ c \in C_n. \tag{15}$$

For load shedding, we impose costs

$$c^{\text{ls}} > \max\{c^{\text{var}}_g : g \in G^{\text{all}}_n, n \in N^{\text{core}}\}.$$

The third-level problem minimizes reallocation costs given by

$$\begin{aligned}\psi_3 :=& \sum_{t\in T}\sum_{n\in N^{\text{core}}} \tau_t \int_{d^{\text{red}}_{n,t}}^{d^{\text{spot}}_{n,t}} p_{n,t}(\omega)\,\mathrm{d}\omega \\ &+ \sum_{t\in T}\sum_{n\in N^{\text{core}}} \tau_t \left(\sum_{g\in G^{\text{conv}}_n} c^{\text{var}}_g \left(q^{\text{red}}_{g,t} - q^{\text{spot}}_{g,t}\right) + \sum_{g\in G^{\text{bu}}_n} c^{\text{var}}_g q^{\text{red}}_{g,t} \right) \\ &+ \sum_{t\in T}\sum_{n\in N^{\text{core}}} \tau_t c^{\text{ls}} d^{\text{ls}}_{n,t}.\end{aligned}$$

Note that, by Assumption 1, this is a convex function in the third-level variables.

The quantities after redispatch have to fulfill all physical transmission constraints within the core market. This includes Kirchhoff's first law that ensures power balance at every core node $n \in N^{\text{core}}$ and time period $t \in T$:

$$d^{\text{red}}_{n,t} + \sum_{l\in\delta^{\text{out}}_n} f^{\text{red}}_{l,t} = \sum_{g\in G^{\text{all}}_n} q^{\text{red}}_{g,t} + \sum_{l\in\delta^{\text{in}}_n} f^{\text{red}}_{l,t}. \tag{16}$$

In addition, Kirchhoff's second law determines—according to the expansion plan specified at the first level—the voltage angles $\theta_{n,t}$, $t \in T$, $n \in N^{\text{core}}$, in the network:

$$f^{\text{red}}_{l,t} = B_l(\theta_{n,t} - \theta_{m,t}) \qquad \text{for all } l = (n,m) \in L^{\text{ex}} \cap L^{\text{core}},\ t \in T, \tag{17a}$$

$$f^{\text{red}}_{l,t} = y_l B_l(\theta_{n,t} - \theta_{m,t}) \qquad \text{for all } l = (n,m) \in L^{\text{new}} \cap L^{\text{core}},\ t \in T. \tag{17b}$$

Note that the indicator constraint (17b) is parameterized by the first-level decision and linear in the third-level variables. A formulation that is linear in all variables can be obtained by a reformulation using big-Ms. Since the solution approach presented in Section 4 is not harmed by the nonlinear indicator formulation, we avoid big-Ms by using (17).

In order to obtain unique physical solutions, we have to fix the voltage angle at an arbitrary reference node $\hat{n} \in N^{\text{core}}$ in every time period:

$$\theta_{t,\hat{n}} = 0 \quad \text{for all } t \in T. \tag{18}$$

Furthermore, all transmission flows are limited by lower and upper bounds, i.e.,

$$-\bar{f}_l \le f^{\text{red}}_{l,t} \le \bar{f}_l \qquad \text{for all } l \in L^{\text{ex}} \cap L^{\text{core}},\ t \in T, \tag{19a}$$

$$-\bar{f}^{\text{mod}}_l y_l \le f^{\text{red}}_{l,t} \le \bar{f}^{\text{mod}}_l y_l \qquad \text{for all } l \in L^{\text{new}},\ t \in T. \tag{19b}$$

The latter constraint also guarantees that only those lines are used at the redispatch level that are built in the first level.

In addition to demand and production bounds of existing and candidate generators,

$$0 \le d^{\text{red}}_{n,t} \qquad \text{for all } n \in N^{\text{core}},\ t \in T, \tag{20a}$$

$$0 \le q^{\text{red}}_{g,t} \le \omega_{g,t} \bar{q}^{\text{fix}}_g \qquad \text{for all } g \in G^{\text{ex}}_n,\ n \in N^{\text{core}},\ t \in T, \tag{20b}$$

$$0 \le q^{\text{red}}_{g,t} \le \omega_{g,t} \bar{q}^{\text{mod}}_g x_g \qquad \text{for all } g \in G^{\text{new}}_n \cap G^{\text{res}}_n,\ n \in N^{\text{core}},\ t \in T, \tag{20c}$$

$$0 \le q^{\text{red}}_{g,t} \le \omega_{g,t} \bar{q}_g \qquad \text{for all } g \in G^{\text{new}}_n \cap G^{\text{conv}}_n,\ n \in N^{\text{core}},\ t \in T, \tag{20d}$$

backup generators are constrained by

$$0 \le q^{\text{red}}_{g,t} \le \omega_{g,t} \bar{q}_g \quad \text{for all } g \in G^{\text{bu}}_n,\ n \in N^{\text{core}},\ t \in T. \tag{21}$$

The capacities $\bar{q}_g$ of backup generators $g \in G^{\text{bu}}_n$ are determined by the regulator and thus belong to the first level. In total, the redispatch problem reads

$$\min \quad \psi_3 \quad \text{s.t.} \quad (15)\text{–}(21). \tag{22}$$

For fixed first- and second-level variables, this problem is a convex-quadratic minimization problem over polyhedral constraints.

Altogether, we are facing a nonconvex mixed-integer nonlinear trilevel problem, where the first level is a nonconvex MINLP and the second and third level are concave maximization or convex minimization problems, respectively. Note that the nonconvexities in the first-level objective function (5) stem from the modeling of trans-regional payments and add significant difficulties to the already challenging trilevel model. The overall model structure and the dependencies between the levels are depicted in Figure 2.

Later, in Section 5, we analyze the welfare effects that stem from the regional planning of the regulator in the core market. We therefore also compute supra-regional solutions, in which the regulator of the core market acts in favor of the full market. This can be achieved by changing the objective function of the first-level model to

$$\begin{aligned}\psi_1 := &\sum_{t\in T}\sum_{n\in N} \tau_t \left(\int_0^{d^{\text{red}}_{n,t}} p_{n,t}(\omega)\,\mathrm{d}\omega - \sum_{g\in G^{\text{all}}_n} c^{\text{var}}_g q^{\text{red}}_{g,t} \right) - \sum_{l\in L^{\text{new}}} c^{\text{mod}}_l y_l \\ &- \sum_{n\in N} \left(\sum_{g\in G^{\text{res}}_n \cap G^{\text{new}}_n} c^{\text{inv}}_g \bar{q}^{\text{mod}}_g x_g + \sum_{g\in G^{\text{conv}}_n \cap G^{\text{new}}_n} c^{\text{inv}}_g \bar{q}_g + \sum_{g\in G^{\text{bu}}_n} c^{\text{inv}}_g \bar{q}_g \right) \\ &- \sum_{t\in T}\sum_{n\in N^{\text{core}}} \tau_t c^{\text{ls}} d^{\text{ls}}_{n,t}.\end{aligned} \tag{23}$$

Compared to (5), all nonconvex terms modeling trans-regional payments cancel out and we take the sum over all nodes for consumers surplus and producer costs instead of only considering the core-region nodes. As a consequence, (23) is a concave-quadratic function.

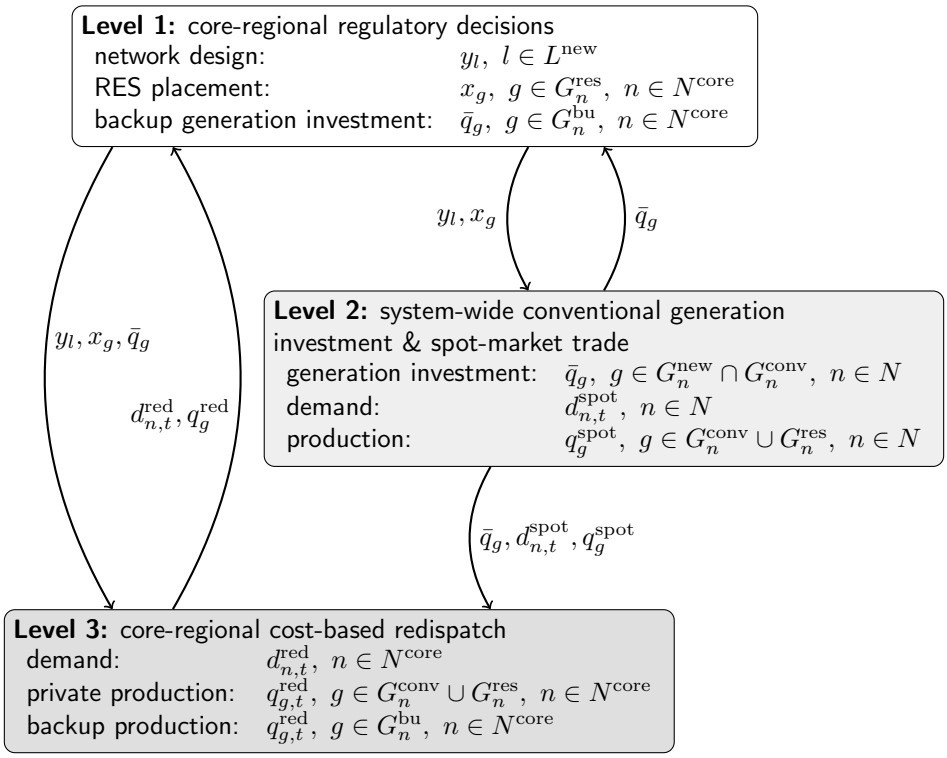

FIGURE 2. Structure of the trilevel market model.

3. A NODAL-PRICING BILEVEL MODEL

Besides the trilevel model stated in Section 2, which models a zonal-pricing regime, we also consider a nodal-pricing regime. This results in a bilevel optimization problem, in which the first level is similar to the first-level problem in Section 2.2. The difference is that, in a nodal-pricing environment, the traded spot-market quantities are feasible w.r.t. transport through the network and, thus, redispatch and load shedding is not required. Moreover, the modeling of backup generators is also not needed in the first level. The lower-level problem of the nodal-pricing bilevel problem is a combination of Problem (13) and (22). Note, at this point, that the market area considered by the regulator (level one) and the generators (level two) is different, such that the problem to be considered is a genuine bilevel problem. The modeling in this section builds on and combines previous work on (i) long-term investment planning models, which addresses transmission and generation investment for one regional electricity market with nodal pricing (Sauma and Oren 2009; Spyrou et al. 2017) with (ii) the objective for regional optimization as implemented in the seams literature on transmission investment games between multiple regions with nodal pricing. Note that the latter generally abstracts from investment in conventional and renewable generation capacity; see e.g., Huppmann and Egerer (2015) and Tohidi, Hesamzadeh, and Regairaz (2018). In more detail,

the upper level of the nodal-pricing problem is given by

$$\max \quad \sum_{t\in T}\sum_{n\in N^{\mathrm{core}}} \tau_t \left(\int_0^{d_{n,t}} p_{n,t}(\omega)\,\mathrm{d}\omega - \sum_{g\in G_n^{\mathrm{conv}}} c_g^{\mathrm{var}} q_{g,t} \right) \tag{24a}$$

$$- \sum_{n\in N^{\mathrm{core}}} \left(\sum_{g\in G_n^{\mathrm{res}}\cap G_n^{\mathrm{new}}} c_g^{\mathrm{inv}} \bar{q}_g^{\mathrm{mod}} x_g + \sum_{g\in G_n^{\mathrm{conv}}\cap G_n^{\mathrm{new}}} c_g^{\mathrm{inv}} \bar{q}_g \right)$$

$$- \sum_{l\in L^{\mathrm{new}}} c_l^{\mathrm{mod}} y_l + \sum_{t\in T} \sum_{l=(n,m)\in \delta^{\mathrm{out}}_{N^{\mathrm{core}}}} \tau_t \left(s_n^{\mathrm{cong}} \pi_{m,t} + s_m^{\mathrm{cong}} \pi_{n,t} \right) f_{l,t}$$

$$\text{s.t.} \quad (1)\text{–}(3) \tag{24b}$$

and the lower level reads

$$\max \quad \sum_{t\in T}\sum_{n\in N} \tau_t \left(\int_0^{d_{n,t}} p_{c,t}(\omega)\,\mathrm{d}\omega - \sum_{g\in G_n^{\mathrm{conv}}} c_g^{\mathrm{var}} q_{g,t} \right) \tag{25a}$$

$$- \sum_{n\in N} \sum_{g\in G_n^{\mathrm{new}}\cap G_n^{\mathrm{conv}}} c_g^{\mathrm{inv}} \bar{q}_g$$

$$\text{s.t.} \quad d_{n,t} + \sum_{l\in \delta_n^{\mathrm{out}}} f_{l,t} = \sum_{g\in G_n^{\mathrm{all}}} q_{g,t} + \sum_{l\in \delta_n^{\mathrm{in}}} f_{l,t} \quad \text{for all } n\in N,\ t\in T \tag{25b}$$

$$f_{l,t} = B_l(\theta_{n,t} - \theta_{m,t}) \quad \text{for all } l=(n,m)\in L^{\mathrm{ex}},\ t\in T, \tag{25c}$$

$$f_{l,t} = B_l y_l(\theta_{n,t} - \theta_{m,t}) \quad \text{for all } l=(n,m)\in L^{\mathrm{new}},\ t\in T \tag{25d}$$

$$\theta_{t,\hat{n}} = 0 \quad \text{for all } t\in T, \tag{25e}$$

$$-\bar{f}_l \le f_{l,t} \le \bar{f}_l \quad \text{for all } l\in L^{\mathrm{ex}},\ t\in T, \tag{25f}$$

$$-\bar{f}_l^{\mathrm{mod}} y_l \le f_{l,t} \le \bar{f}_l^{\mathrm{mod}} y_l \quad \text{for all } l\in L^{\mathrm{new}},\ t\in T, \tag{25g}$$

$$\pi_{n,t} = a_{n,t} + b_{n,t} d_{n,t} \quad \text{for all } n\in N,\ t\in T. \tag{25h}$$

$$0 \le d_{n,t} \quad \text{for all } n\in N,\ t\in T, \tag{25i}$$

$$0 \le q_{g,t} \le \omega_{g,t} \bar{q}_g^{\mathrm{fix}} \quad \text{for all } g\in G_n^{\mathrm{ex}},\ n\in N,\ t\in T, \tag{25j}$$

$$0 \le q_{g,t} \le \omega_{g,t} \bar{q}_g^{\mathrm{mod}} x_g \quad \text{for all } g\in G_n^{\mathrm{new}}\cap G_n^{\mathrm{res}},\ n\in N^{\mathrm{core}},\ t\in T, \tag{25k}$$

$$0 \le q_{g,t} \le \omega_{g,t} \bar{q}_g \quad \text{for all } g\in G_n^{\mathrm{new}}\cap G_n^{\mathrm{conv}},\ n\in N,\ t\in T. \tag{25l}$$

The overall problem is a nonlinear mixed-integer bilevel problem, where the upper level is an MINLP and the lower level is a QP for fixed upper-level variables.

4. Solution Approach

Multilevel optimization problems are very hard to solve. Even in their easiest instantiation, i.e., linear-linear bilevel models, they are already strongly NP-hard; see, e.g., Dempe et al. (2015) and Hansen et al. (1992). The model presented in Section 2 contains mainly three additional aspects that make it even harder:

(1) It is a mixed-integer trilevel model.
(2) The first-level objective function (5) is nonconvex.
(3) The linking variables between the first and the third level as well as between the second and the third level are continuous.

In bilevel optimization, one can reformulate a convex lower level by strong duality of convex optimization or by using the Karush–Kuhn–Tucker (KKT) conditions of the lower level. Both approaches yield a nonconvex single-level reformulation. However, the KKT approach allows for a linear reformulation of the nonlinear KKT complementarity conditions using big-M constraints if the lower-level feasible set is polyhedral. This results in a large—and often numerically unstable—single-level problem and this approach has the additional drawback that an appropriate

big-M has to be chosen (Kleinert, Labbé, et al. 2020; Pineda and Morales 2019). Nevertheless, if the upper level is a mixed-integer linear (or quadratic) problem, one can at least try to tackle the reformulation by state-of-the-art MI(Q)P solvers. This type of reformulation technique is also applied to trilevel problems similar to the one considered in this paper in Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019), but with a concave-quadratic first-level objective function. Their approach involves a reduction of the trilevel problem to an equivalent bilevel problem and then uses the above mentioned KKT reformulation to a single-level mixed-integer quadratic problem (MIQP). Grimm, Kleinert, et al. (2019) as well as Kleinert and Schmidt (2019) demonstrate that this single-level reformulation is highly challenging and can be solved reliably only for rather small networks. In the context of the model of the present paper, the first two issues from above additionally render every single-level reformulation a nonconvex mixed-integer nonlinear problem (MINLP)—which is of course much harder to solve than a convex MIQP. We thus refrain from using this approach in this paper.

Issue (3) may sound more like an advantage than a disadvantage on first sight. However, many solution techniques for mixed-integer bilevel (or more general multilevel) problems explicitly rely on integer linking variables; see, e.g., the branch-and-bound based algorithm proposed by Xu and Wang (2014) or the sampling-based algorithm of Lozano and Smith (2017). Furthermore, integer linking variables allow for effective enumeration schemes (see, e.g., Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019)) and specialized branch-and-cut methods; see, e.g., Fischetti, Ljubić, et al. (2017, 2018, 2019) and Tahernejad et al. (2016).

Putting all properties of the model together, it seems hopeless to solve the problem at hand without using a highly problem-specific approach. This approach is presented in the remainder of this section. We first propose equivalent model reformulations, that resolve the third issue and allow for a solution approach that is capable of dealing with the second issue. The latter is strongly based on the Benders-like decomposition approaches developed in Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019), which have also been used, in a different setting, in Ambrosius, Grimm, et al. (2018). To avoid unnecessary duplication of the basic techniques, we only discuss the respective difference in the remainder of this section. All other things that can be done in analogy to the above mentioned papers are given in Appendix B. As a first difference, we need the following lemma that is not given in the former articles.

Lemma 1. *The trilevel problem of Section 2 is equivalent to the trilevel problem*

$$\begin{aligned}
\max\quad & \tilde{\psi}_1 := \psi_1 \\
\text{s.t.}\quad & (1)\text{–}(3) \\
& \max\quad \tilde{\psi}_2 := \psi_2 \\
& \text{s.t.}\quad (8)\text{–}(12) \\
& \qquad \min\quad \tilde{\psi}_3 := \psi_3 + \sum_{n \in N^{\mathrm{core}}} \sum_{g \in G_n^{\mathrm{bu}}} c_g^{\mathrm{inv}} \bar{q}_g \\
& \qquad \text{s.t.}\quad (15)\text{–}(21), (4),
\end{aligned} \tag{26}$$

i.e., the problem in which the variables $\bar{q}_g$ for $g \in G_n^{\mathrm{bu}}, n \in N^{\mathrm{core}}$, and Constraint (4) are moved from the first to the third level and the third-level objective function is adapted accordingly.

Before we prove the lemma, we point out the relationship of the objective functions of the three levels. We use the notation

$$\bar{\psi}_1 = \sum_{l \in L^{\text{new}}} c_l^{\text{mod}} y_l + \sum_{n \in N^{\text{core}}} \sum_{g \in G_n^{\text{res}} \cap G_n^{\text{new}}} c_g^{\text{inv}} \bar{q}_g^{\text{mod}} x_g$$

and

$$\begin{aligned}\bar{\psi}_2 = \sum_{t \in T} \sum_{n \in N^{\text{core}}} \left(\tau_t \int_0^{d_{n,t}^{\text{spot}}} p_{c,t}(\omega)\, \mathrm{d}\omega - \sum_{g \in G_n^{\text{conv}}} c_g^{\text{var}} q_{g,t}^{\text{spot}} \right) \\ - \sum_{n \in N^{\text{core}}} \sum_{g \in G_n^{\text{new}} \cap G_n^{\text{conv}}} c_g^{\text{inv}} \bar{q}_g \\ + \sum_{t \in T} \sum_{l=(n,m) \in \delta^{\text{out}}_{N^{\text{core}}}} \tau_t \frac{\pi_{m,t} + \pi_{n,t}}{2} f_{l,t}^{\text{spot}}.\end{aligned}$$

Using this notation, it holds

$$\psi_1 = \bar{\psi}_2 - \bar{\psi}_1 - \sum_{n \in N^{\text{core}}} \sum_{g \in G_n^{\text{bu}}} c_g^{\text{inv}} \bar{q}_g - \psi_3 = \bar{\psi}_2 - \bar{\psi}_1 - \tilde{\psi}_3 = \tilde{\psi}_1. \tag{27}$$

Proof. Let $s^* = (s_1^*, s_2^*, s_3^*)$ be an optimal solution of the original trilevel problem. By a slight abuse of notation, we further specify the solution of the original first level as $s_1^* = (x^*, y^*, \bar{q}_{\text{bu}}^*)$, where $\bar{q}_{\text{bu}}^*$ denotes the optimal vector of backup generation capacity variables. Then, (x^*, y^*) is feasible for the first level of Problem (26) and s_2^* is optimal for the second level of Problem (26) with fixed (x^*, y^*). In addition, $(\bar{q}_{\text{bu}}^*, s_3^*)$ also minimizes the third level of Problem (26) with fixed (x^*, y^*, s_2^*). To see this, assume that there exists a solution $(\bar{q}'_{\text{bu}}, s'_3)$ of the third level of Problem (26) with fixed (x^*, y^*, s_2^*) that yields $\tilde{\psi}_3(\bar{q}'_{\text{bu}}, s'_3) < \tilde{\psi}_3(\bar{q}_{\text{bu}}^*, s_3^*)$. Then, $(x^*, y^*, \bar{q}'_{\text{bu}}, s_2^*, s'_3)$ is feasible for the original trilevel problem and with (27) it holds

$$\begin{aligned}\psi_1(x^*, y^*, \bar{q}'_{\text{bu}}, s_2^*, s'_3) &= \bar{\psi}_2(s_2^*) - \bar{\psi}_1(x^*, y^*) - \tilde{\psi}_3(\bar{q}'_{\text{bu}}, s'_3) \\ &> \bar{\psi}_2(s_2^*) - \bar{\psi}_1(x^*, y^*) - \tilde{\psi}_3(\bar{q}_{\text{bu}}^*, s_3^*) \\ &= \psi_1(s^*),\end{aligned}$$

which contradicts the optimality of s^*. In total, s^* is feasible for the first level and optimal for the second and third level of Problem (26) and consequently feasible for Problem (26).

On the other hand, let $\tilde{s} = (\tilde{s}_1, \tilde{s}_2, \tilde{s}_3)$ be an optimal solution of Problem (26), with $\tilde{s}_1 = (\tilde{x}, \tilde{y})$ and $\tilde{s}_3$ containing $\tilde{\bar{q}}_{\text{bu}}$. Obviously, $(\tilde{s}_1, \tilde{\bar{q}}_{\text{bu}})$ is feasible for the first-level problem (6) and $\tilde{s}_2$ is optimal for the second-level problem (13) for fixed $\tilde{s}_1$. Furthermore, for fixed $\bar{q}_{\text{bu}} = \tilde{\bar{q}}_{\text{bu}}$ the original third-level problem (22) is—apart from a constant term in the objective function—exactly the third level in Problem (26) for fixed $\tilde{\bar{q}}_{\text{bu}}$. Thus, $\tilde{s}_3$ is optimal for the original third-level problem (22) with fixed $(\tilde{s}_1, \tilde{s}_2, \tilde{\bar{q}}_{\text{bu}})$. In total, $\tilde{s}$ is feasible for the original first-level problem and optimal for the original second- and third-level problem. Consequently, $\tilde{s}$ is feasible for the original trilevel problem.

In summary, we have that s^* feasible and $\tilde{s}$ is optimal for the reformulated trilevel problem (26). Thus, we obtain

$$\psi_1(s^*) \leq \psi_1(\tilde{s}). \tag{28}$$

Further, we know that $\tilde{s}$ is feasible and s^* is optimal for the original trilevel problem, which gives

$$\psi_1(\tilde{s}) \leq \psi_1(s^*). \tag{29}$$

Using both (28) and (29), we obtain $\psi_1(s^*) = \psi_1(\tilde{s})$. Hence, an optimal solution of the original trilevel problem is also optimal for Problem (26) and vice versa. □

Note that in the reformulated Problem (26), the variables $\bar{q}_g$ for $g \in G_n^{\text{bu}}$, $n \in N^{\text{core}}$, are third-level variables. Thus, the only first-level variables present in the second and third level are the integer variables that model investment in transmission lines (1) and renewable generation projects (2). These integer variables can easily be reformulated to binary variables, which is required by our solution technique. For line expansion variables y_l, $l \in L^{\text{new}}$, we introduce binary variables $y_{l,i}^{\text{bin}}$ with $i \in \{1, \dots, r_l := \lfloor \log_2(\bar{y}_l) \rfloor + 1\}$. In addition, we need the constraints

$$y_l = \sum_{i=1}^{r_l} 2^{r_l - 1} y_{l,i}^{\text{bin}}. \tag{30}$$

Similarly, we introduce binary variables $x_{g,i}^{\text{bin}}$ for all x_g, $g \in G_n^{\text{res}} \cap G_n^{\text{new}}$, $n \in N^{\text{core}}$, with $i \in \{1, \dots, r_g := \lfloor \log_2(\bar{x}_g) \rfloor + 1\}$ and the set of constraints

$$x_g = \sum_{i=1}^{r_g} 2^{r_g - 1} x_{g,i}^{\text{bin}}. \tag{31}$$

With these reformulations, we are facing a mixed-integer nonlinear trilevel problem with the following structure: The first-level constraints only depend on genuine first-level integer (and binary) variables. The second-level problem depends on binary variables of the first-level due to Reformulation (30), but not on variables of the third level. Similarly, the third-level problem now depends on binary first-level and continuous second-level variables but—due to Lemma 1—not on continuous first-level variables anymore. Only the nonlinear first-level objective function connects all three levels. These coupling properties are exactly the ones that are required to apply the Benders-like decomposition as it is developed in Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019). The structure of this decomposition algorithm is depicted in Algorithm 1. In a nutshell, the mechanism is the following.

Algorithm 1: Benders-like decomposition of Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019).

Input: The trilevel problem of Section 2.
Output: A globally optimal solution for the trilevel problem.

```
while ψ_1^LB < ψ_1^UB do
    Solve the Benders master problem, obtain corresponding fist-level binary
      variables, and let ψ_1^UB denote the corresponding objective value.
    Solve the second-level problem (13) with fixed first-level binary variables.
    Solve the third-level problem (22) with fixed binary first-level and
      continuous second-level variables.
    Evaluate ψ_1 for given first-, second- and third-level solutions.
    Add Benders optimality cuts.
    if ψ_1 > ψ_1^LB then update ψ_1^LB ⟵ ψ_1.
```

With the help of a Benders master problem, which is a relaxation of the full trilevel problem, we compute promising first-level solutions and an upper bound ψ_1^{UB} for the trilevel objective function (5). In particular, this Benders master problem is a comparably simple MILP because it linearly overestimates the nonlinear objective function (5); see Appendix B for details. The solution of the master problem, i.e., the binary first-level variables, can be fixed in the Benders subproblem, which in our case is a bilevel problem consisting of the original second- and third-level problem.

Since the solution of the second level does not depend on the third-level solution, the second and third level can be solved subsequently. Thus, solving the subproblem can be done in polynomial time by solving two QPs. In order to obtain a correct approach, it is necessary that the solution of the second-level problem is unique. However, the second-level solution may be ambiguous, e.g., due to generators with the same cost structure. Within one bidding zone, equilibria can be selected via tie breaking rules as proposed in Ambrosius, Grimm, et al. (2018). In case of equivalent cost structures of generators across zones, ambiguities may occur in time periods in which inter-zonal transmission lines are non-binding. Since in this case no reasonable tie breaking can be applied, we exclude such situations; see also Section 5.

Subsequently solving the second- and third-level problem for a fixed master solution yields a feasible solution of the trilevel problem. Thus, we can evaluate the nonlinear first-level objective function to obtain a lower bound ψ_1^{LB}. Furthermore, each feasible solution of the trilevel problem provides no-good-cut-like optimality cuts. When added to the master problem, these cuts enforce the objective function value ψ_1^{LB} if a master solution is considered for the second time. We state the optimality cuts in Appendix B. The algorithm stops with a globally optimal solution, when the upper bound ψ_1^{UB} and lower bound ψ_1^{LB} meet.

Theorem 1. *Algorithm 1 terminates after a finite number of iterations and returns a globally optimal solution for trilevel problem of Section 2.*

The proof of this theorem can be obtained in analogy to the proofs given in Grimm, Kleinert, et al. (2019) and Kleinert and Schmidt (2019). We thus refrain from formally stating it but only sketch the main ideas, which follow directly from the discussions above. Every solution of the master problem yields an upper bound and every solution of the corresponding subproblem yields a lower bound of the trilevel problem. Thus, whenever a master solution is visited for the second time, the termination criterion is reached and the algorithm stops. The finiteness then follows from the finite number of integer-feasible solutions of the master problem (or the first-level problem, respectively). Correctness follows from the construction of the Benders cuts.

In Grimm, Kleinert, et al. (2019) as well as Kleinert and Schmidt (2019), this Benders-like decomposition proved to be numerically much more stable and effective compared to an MIQP single-level reformulation. As already mentioned, this effect would be even more drastic in our application, because the nonconvex objective function of the first level adds further nonconvexity to the single-level reformulation. In addition, algorithms for nonconvex mixed-integer problems typically only yield ε-optimal solutions. In contrast, Algorithm 1 decomposes the problem in a way, such that the nonconvexity only needs to be evaluated. The algorithm is thus not affected at all by the additional complexity that stems from a correct modeling of the interaction with neighboring markets and yields the global optimal solution.

Finally, it is easy to see that the nodal-pricing bilevel model of Section 3 can be tackled with a suitably adapted version of Algorithm 1.

5. Test case

As described in the last sections, we consider a regulator of a core region that decides on regional optimal investment in RES and transmission capacity within her jurisdiction to maximize regional welfare, i.e., the welfare of the core region. In Section 2, we modeled this for a uniform- or zonal-pricing regime, whereas in Section 3, we modeled a nodal-pricing regime. In this and the next section, we analyze the effects of regional planning of the core region's regulator compared to supra-regional planning for the different (uniform, zonal, and nodal pricing) congestion-pricing schemes.

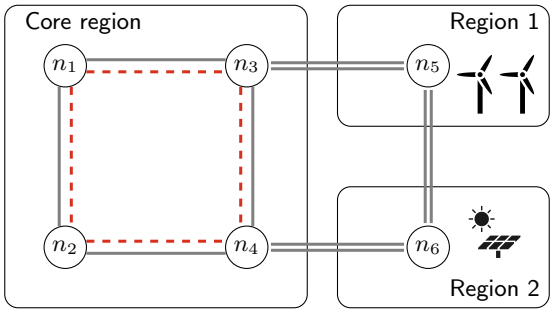

FIGURE 3. Network topology with existing (solid) and candidate (dashed/red) transmission lines

We apply our setup to the simplistic electricity network given in Figure 3. The considered test case does not resemble a specific real-world electricity system but serves as an academic example, which represents general characteristics of electricity markets regarding, e.g., the spatial distribution and temporal characteristics of demand, the cost structure for conventional technologies, and assumptions on the spatial potential and temporal availability of renewable technologies. This section together with Table 10 in Appendix C provides a complete overview of the input data of the considered test case. All data described in the following is normed to 1 MW of peak-load demand of the core region. The core region consists of four nodes, i.e., $N^{\text{core}} = \{n_1, \ldots, n_4\}$. In addition, we have two neighboring (surrounding) markets $N^{\text{sur}} = \{n_5, n_6\}$. All transmission lines have an equal susceptance of 1 S, and a capacity of 0.05 MW. The network topology in Figure 3 consists of four intra-regional connections within the core region and three inter-regional connections that connect the core region to the neighboring markets as well as the two neighboring markets. In the initial setting, each intra-regional connection is equipped with one transmission line and each inter-regional connection with two parallel transmission lines (solid lines). In addition, the regulator of the core region can decide on investment in intra-regional (dashed/red) transmission lines with the same physical properties as the existing lines and an annuity of investment cost of 1850 EUR. This corresponds to an average of 4.2 EUR/MWh at full utilization of line capacity for the entire year. It is not possible to invest in inter-regional transmission lines.

For the core region, we assume a green field approach, i.e., no generation capacity is installed yet. The capacity of renewables is determined endogenously by the regulator; see (2). As stated in Constraint (3), the regulator has to satisfy a specific renewable investment target. In particular, we assume that the aspired political renewable target is 41 % of the annual reference demand and that the minimal required realization is 39 %. Each renewable project $g \in G_n^{\text{new}} \cap G_n^{\text{res}}$, $n \in N^{\text{core}}$, has a capacity $\bar{q}_g^{\text{mod}}$ equivalent to 5 % of the annual reference demand. Table 1 summarizes the annuity of investment cost and variable generation cost of all technologies. These values translate into levelized cost of electricity at the nodes with best resource quality for wind and PV as indicated in Table 2. Wind has the lowest cost at n_3 (47.5 EUR/MWh), compared to PV at n_4 (54 EUR/MWh). For both technologies, we assume less suitable wind and solar conditions at the other nodes which induce higher investment costs in order to provide the same annual generation output. For wind, n_1 ranks second in resource quality (+ 32 % markup) followed by n_4 (+ 60 % markup). For PV we assume smaller differences in resource quality between the three nodes (+ 3 % markup at n_1 and + 7 % markup at n_3). It is not possible to invest in either wind or PV at the main demand node n_2.

TABLE 1. Economic parameters for conventional technologies

	Unit	CCGT	GT	Wind	PV
Annuity investment cost	EUR/MW	69 900	32 500	71 500	61 800
Variable generation cost	EUR/MWh	46.8	76.2	0.0	0.0

TABLE 2. Levelized cost of electricity (LCOE) at the nodes in the core region (in EUR/MWh) for investment in wind and PV

	n_1	n_2	n_3	n_4
Wind	62.5	—	47.5	76.0
PV	55.5	—	58.0	54.0

TABLE 3. Structure of time periods with respective probability.

	No	Entries (frequency)
Seasons	2	winter (0.5), summer (0.5)
Demand levels	6	d_1/d_6 (0.1), d_2–d_5 (0.2)
Wind	3	w_1 (0.1), w_2 (0.8), w_3 (0.1)

In contrast to the core region, we assume an exogenous renewable scenario for the neighboring markets with 0.98 MW wind capacity installed at node n_5 and 0.43 MW PV capacity installed at n_6; see Figure 3.

Generation investment in conventional technologies, i.e., combined-cycle gas turbines (CCGT) and gas turbines (GT) power plants, is possible at all nodes.

We implement the same generation technology (i.e., CCGT, GT, and wind/PV) with a very small variance ($\pm 10^{-3}$ EUR/MWh) in variable costs between different bidding zones to guarantee unique spot-market results; see also the discussion in Section 4 and Grimm, Schewe, et al. (2017) for more details on uniqueness of spot-market results. For backup generators on the redispatch level we assume the same cost as for GT and for load shedding the value of lost load of 3000 EUR/MWh.

The temporal time resolution of the test case includes 36 time periods (Table 3), which represent two seasons (winter and summer), six different demand levels per season from d_1 (peak) to d_6 (off-peak), and three different wind capacity factors from w_1 (highest) to w_3 (lowest). In combination, this makes a total of 36 time periods, which occur at different frequency and scale in one representative year. Each combination of season and demand hour is attributed with an individual capacity factor for PV. Linear inverse demand functions at each node are derived for the time periods with the help of a reference demand, a reference price, and a point elasticity of demand ($\varepsilon = -0.1$). The peak reference demand is 1.0 MW in the core region (0.2 MW at n_1, 0.5 MW at n_2, 0.1 MW at n_3, and 0.2 MW at n_4) and 0.4 MW for each neighboring region. Table 10 in Appendix C provides an overview on reference demand levels, reference prices, and capacity factors for wind as well as PV in each time period.

6. RESULTS

We now compare the optimal regional investment decisions, i.e., welfare-maximizing decisions of the core region, with optimal supra-regional decisions that maximize the system-wide welfare. Maximal core-region welfare is obtained by solving the model with the regional welfare objective as described in Section 2 or

Section 3, depending on the congestion-pricing scheme. In this case, we assume a 50:50 splitting of the congestion rents, i.e., $s_n^{\text{cong}} = 0.5$ for all $n \in N$. We explicitly point out that welfare gains and losses in the neighboring markets do not affect the decisions of the core-region's regulator. Maximal system-wide welfare can be obtained by solving the same models but with the system-wide first-level objective function (23). We are interested in the following four different bidding zone configurations: a single uniform bidding zone ($\{n_1, n_2, n_3, n_4\}$), two bidding zones ($\{n_1, n_2\}$, $\{n_3, n_4\}$ or $\{n_1, n_3\}$, $\{n_2, n_4\}$), and nodal pricing ($\{n_1\}$, $\{n_2\}$, $\{n_3\}$, $\{n_4\}$).

Before we discuss results for welfare levels per region, network and RES investments in the core region, and distributional effects including electricity prices, we briefly discuss some computational aspects of our analysis.

All computational experiments have been executed on a compute cluster using compute nodes with Intel Xeon E3-1240 v6 CPUs with 4 cores, 3.7 GHz, and 32 GB RAM; see Regionales Rechenzentrum Erlangen (2020) for more details. We implemented the algorithm in Python 2.7 and used Gurobi 8.1 to solve all optimization problems. As mentioned in Section 4, the Benders-like decomposition approach computes a global optimum of the trilevel and bilevel problems of Section 2 and Section 3, respectively. The running time of the algorithm depends on (i) the running time per iteration of the algorithm and (ii) the number of iterations needed to compute a global optimum. The former is mainly driven by the size of the subproblems, i.e., the size of the original second- and third-level problem. Since the subproblems can be solved in polynomial time, it can be expected that the running time per iteration scales quite well with larger networks or bigger sets of time periods T. In contrast, the number of iterations scales exponentially with the integer decisions of the first-level problem. It can thus be expected that larger networks with more modules of candidate lines and modules of renewable energy systems, modeled as integer decisions $y_l \in \{0, \dots, \bar{y}_l\}$ and $x_g \in \{0, \dots, \bar{x}_g\}$ in Section 2, require significantly more computation time. With regard to median and mean running times—which are around 5.7 h and 9.3 h, respectively—for the various configurations that we consider in this section, tackling larger instances may be difficult. On the other hand, we observe that optimal solutions are found for many instances already after a few seconds or minutes, while the best bound obtained by the master problem only improves very slowly. Thus, we see several possibilities to apply the approach to larger instances: (i) Using (potentially) suboptimal solutions and stop the algorithm after a certain time limit, (ii) tightening the master problem to obtain better bounds, and (iii) develop stronger Benders optimality cuts. Especially the latter two aspects are relevant from a methodological point of view but are out of scope of this paper.

6.1. **Change in Welfare Levels for Regional Planning.**

Result 1. *Regional investment planning allows for higher welfare levels in the core region than supra-regional planning, but it decreases system welfare and causes significant external effects in neighboring markets. Depending on the market design in the core region, adjacent regions can either gain or lose.*

Table 4 states changes in the annual welfare levels for regional compared to supra-regional investment planning. The values represent an electricity system with a peak demand of 1 MW in the core region and 0.4 MW in both adjacent regions.

Except for one case with two bidding zones (north-south), welfare in the core region increases for regional planning whereas overall system welfare decreases. The core region has a higher potential to increase its welfare for nodal pricing (+122 EUR/yr) than for uniform pricing (+26 EUR/yr). However, one configuration with two bidding zones (west-east) provides an even higher welfare gain (+726 EUR/yr).

TABLE 4. Welfare effects in case of regional compared to supra-regional planning for different bidding zone configurations and for nodal pricing (in EUR/yr).

Congestion-pricing scheme	Core region $\{n_1, \ldots, n_4\}$	Region 1 $\{n_5\}$	Region 2 $\{n_6\}$	Total
One zone	+26	-413	+378	-9
Two zones (north-south)	—	—	—	—
Two zones (west-east)	+726	+708	-1468	-34
Nodal pricing (four nodes)	+122	-259	-153	-290

The neighboring regions have to pay for the sum of losses in system welfare and welfare gains in the core region. Depending on the bidding zone configuration, one of the adjacent regions might also benefit from regional planning in the core region. For one bidding zone in the core region, region 2 is by far the single biggest winner (+378 EUR/yr), which in turn results in higher welfare losses for region 1 (-413 EUR/yr). In one case with two bidding zones, the core region (+726 EUR/yr) and region 1 (+708 EUR/yr) see even higher welfare gains which in result causes an even higher loss in welfare for region 2 (-1468 EUR/yr). Nodal pricing with regional planning results in a lower welfare level for both adjacent regions and also in by far the highest losses in absolute system welfare (-290 EUR/yr).

6.2. **Investment in Generation and Transmission Capacity.**

Result 2. *The regulator in the core region takes different decisions on investment in RES and/or transmission capacity within a regional compared to a supra-regional planning approach which also alters the incentives for private investment in generation capacity. For instance, under regional planning we observe increased network investment; see Figure 4.*

Table 4 shows investment decisions for regional planning (left column) and supra-regional planning (right column) for different bidding zone configurations. For each bidding zone configuration, differences in the investment decisions are depicted in red.

In case of a single bidding zone in the core region, supra-regional planning results in equal shares for wind and PV with four wind projects at the node with best wind conditions (n_3) and two PV projects each at the nodes with best (n_4) and second-best (n_1) condition for PV, as well as significant network investments of eight lines. For regional planning, the regulator can increase welfare in the core region by replacing PV (n_1) with additional wind (n_3) and investment in one additional transmission line.

Both cases with two bidding zones and supra-regional planning see more wind at n_3 and transmission investment only within but not between bidding zones in the core region. In the case with north-south bidding zones, the regulator has no incentive to change the investment plan for regional planning. For west-east bidding zones, regional planning shifts wind from the eastern bidding zone (n_3) to PV in the western bidding zone (n_1).

For nodal pricing, supra-regional planning suggests the same RES investment as two bidding zones but significantly lower transmission investment (only one line). Regional planning further increases wind capacity at n_3 (cheapest option) and invests in additional transmission capacity for wind integration towards n_4.

Welfare optimal decisions of the regulator on RES placement and network expansion anticipate private investments in conventional generation capacity. Depending

TABLE 5. Private investment in conventional generation capacity for supra-regional planning and differences in case of regional planning (Δ values)

		Core region				Region 1	Region 2
		$\{n_1\}$	$\{n_2\}$	$\{n_3\}$	$\{n_4\}$	$\{n_5\}$	$\{n_6\}$
One zone		Zone 1					
	CCGT	0.168	0.168	0.168	0.168	0.158	0.228
	GT	0.087	0.087	0.087	0.087	0.065	0.000
	Δ CCGT	-0.003	-0.003	-0.003	-0.003	0.000	0.000
	Δ GT	-0.003	-0.003	-0.003	-0.003	-0.015	0.000
Two zones		Zone 1		Zone 2			
	CCGT	0.270	0.270	0.062	0.062	0.158	0.228
	GT	0.048	0.048	0.120	0.120	0.050	0.000
	Δ CCGT	+0.001	+0.001	+0.004	+0.004	0.000	0.000
	Δ GT	-0.001	-0.001	+0.007	+0.007	+0.015	0.000
Nodal pricing		Nodal core region					
	CCGT	0.161	0.390	0.021	0.195	0.118	0.168
	GT	0.000	0.035	0.112	0.082	0.068	0.086
	Δ CCGT	0.000	-0.007	-0.021	+0.016	+0.001	0.000
	Δ GT	0.000	+0.007	-0.054	-0.082	+0.031	-0.033

of the regulator's planning objective, i.e., on supra-regional or regional level, location and technology for private investments can differ considerable; see Table 5. Wind capacity compared to PV has always at least a small availability in hours of peak demand. More wind than PV for regional planning (one bidding zone and nodal pricing) therefore allows lower investments in conventional capacity (vice versa for two bidding zones). In case of zonal pricing, changes in conventional generation investment can be attributed to the different RES investment choices as no transmission investment takes place between bidding zones in the core region. For nodal pricing, more wind and network capacity, in case of regional planning, results in more variation of generations investments by private investors (location and technology) and larger spill-over effects on neighboring markets due to the physical representation of electricity flows in nodal electricity prices.

6.3. **Price Effects and Distributional Effects under Regional and Supra-regional Planning.**

Result 3. *Depending on the congestion-pricing scheme, the regulator follows different strategies to increase welfare in the core region for regional planning. Distributional effects for stakeholders within the core region can be significantly higher than welfare gains and questions of internal cost allocation arise in case of multiple bidding zones or nodal pricing.*

There are different effects that have implications on the welfare in the core region and motivate the regulator's investment decisions in RES capacity and transmission lines in the regional setting. In the following, we describe all aspects regarding costs and rents, which jointly result in the welfare effects for the individual market regions.

First of all, following a specific investment plan in the core region comes at a certain cost which depends on RES investment (renewable costs), i.e., the choice of

FIGURE 4. Investment in RES capacity and transmission lines in the core region for supra-regional and regional planning (in case of uniform pricing, zonal pricing, and nodal pricing).

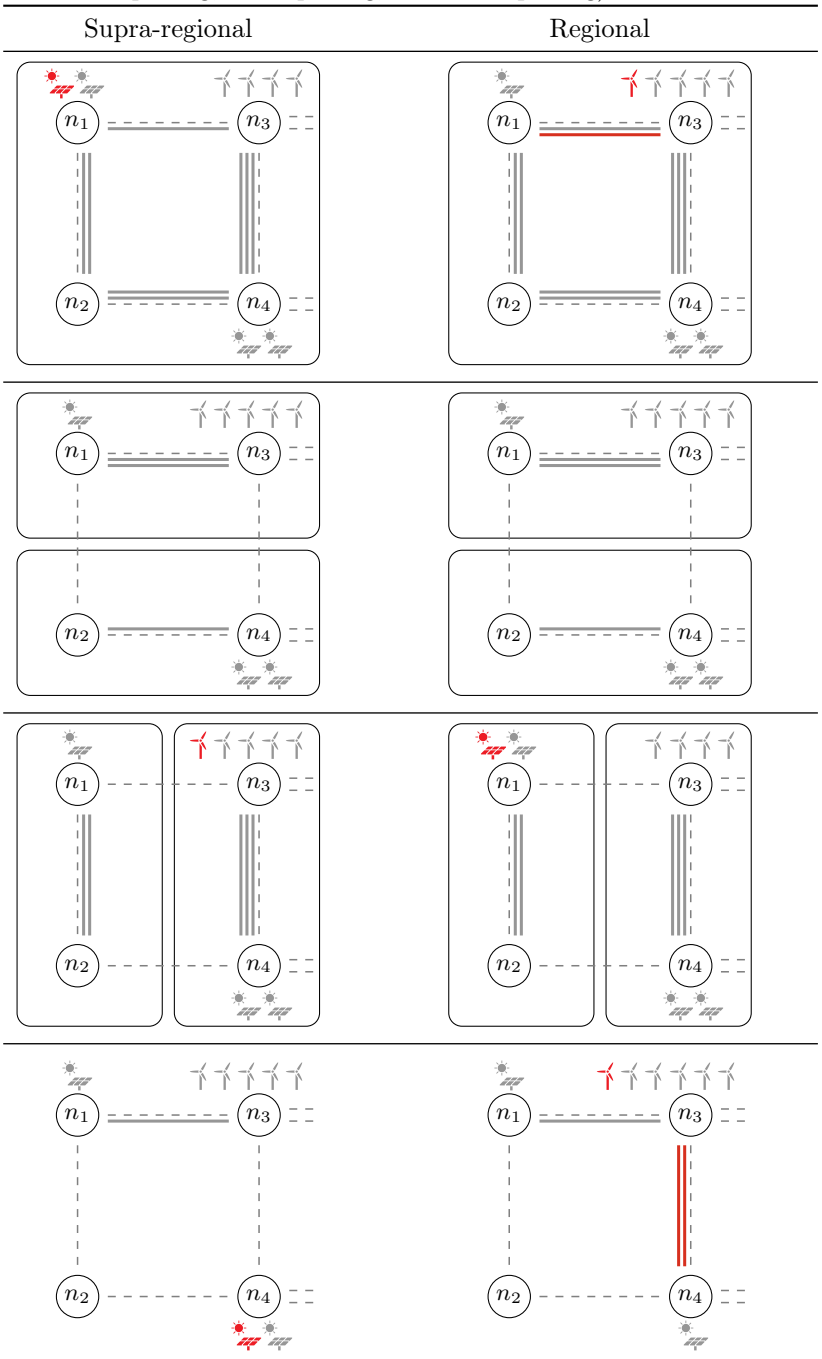

TABLE 6. Distributional effects of regional compared to supra-regional planning for two bidding zone (in EUR/yr)

	Zone 1 $\{n_1, n_2\}$	Zone 2 $\{n_3, n_4\}$	Core region $\{n_1, \ldots, n_4\}$	Region 1 $\{n_5\}$	Region 2 $\{n_6\}$
Renewable cost	17 016	-14 563	2453		
Network cost	0	0	0		
Consumer rent	61	-1828	-1767	-2280	-1718
Network rent	-455	-626	-1081	-150	-281
Renewable rent	15 003	-8724	6279	3139	531
Redispatch cost	-254	257	4		
Backup cost	248	0	248		
Welfare	-2402	3128	726	708	-1468

technology (wind or PV) and their location, as well as on transmission investment, where each additional line increases costs in the core region (network cost). In addition, initial investment decisions in the core region alter the market equilibrium, which includes private investment in conventional generation capacity in the entire electricity system. With a new market equilibrium, electricity prices and stakeholder rents change within the core region but also in neighboring markets. While the market equilibrium under perfect competition enforces a zero-profit condition for private generation companies, consumers benefit from lower prices (consumer rent), RES capacity benefits from higher prices in hours of production (renewable rent), and trade constraints generate congestion rents at the adjacent zones or nodes (network rent). Finally, infeasibility of market outcomes due to internal network congestion within bidding zones may require adjustments (redispatch cost) and investment in backup capacity (backup cost).

For two (west-east) bidding zones, see Table 6, the regulator does not take different network investment choices for regional as compared to supra-regional planning (no change in network cost) but decides to invest less in wind at n_3 (zone 2) and more in PV at n_1 (zone 1), which gives rise to higher renewable cost in the core region by 2453 EUR/yr. While this shift causes lower consumer and network rents as well as higher costs for backup capacity, market payments for RES are significantly higher in case of regional planning (+6279 EUR/yr), leading to an overall welfare gain in the core region.

Within zone 2 ($\{n_3, n_4\}$), lower wind generation at n_3 in case of regional planning (due to lower wind investment, see Table 4) leads to higher electricity prices in about 750 hours; see Figure 5b. Consumer rent (-1828 EUR/yr) as well as price differences with neighboring zones are lower in case of regional planning, resulting in lower network rents (-626 EUR/yr). On the contrary, higher prices lead to higher renewable rent per unit of the remaining wind generation in zone 2. Note, however, that fewer wind capacity is built under regional planning, which leads to a reduction in absolute renewable rent. This rent reduction is significantly lower than the reduction in renewable cost; see Table 6. In zone 1 ($\{n_1, n_2\}$), additional PV capacity under regional planning leads to lower prices and together with lower system peak prices results in a slightly higher consumer rent. However, the network rent is lower than under supra-regional planning and the higher renewable rent does not cover the additional renewable cost for PV at n_1. Overall, welfare gains in the core region are not distributed evenly. While overall welfare effects of regional planning are positive

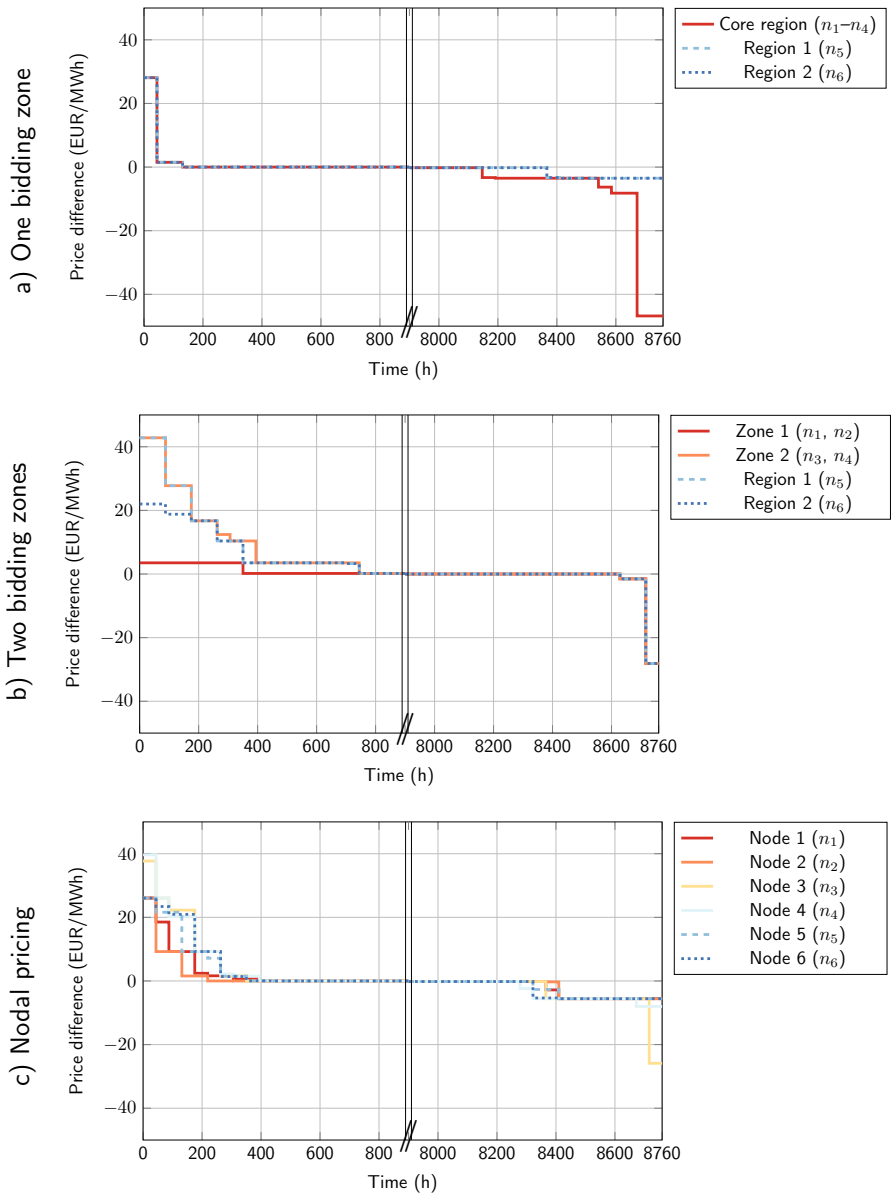

FIGURE 5. Ordered price differences between the regional as compared to the supra-regional scenario ($p^{\text{regional}} - p^{\text{supra-regional}}$)

in zone 2 (+3128 EUR/yr) and negative in zone 1 (-2402 EUR/yr), the direct price effects in the spot market result in lower (higher) consumer rent in zone 2 (zone 1).

Table 6 illustrates that welfare effects in neighboring markets are limited to price effects on consumer rent, network rent, and renewable rent. While the consumer and the network rent decrease in both neighboring regions due to spill-over effects of higher market prices in zone 2, the renewable rent increases much more in region 1 (+3139 EUR/yr) than in region 2 (+531 EUR/yr). The partial shift from wind to PV in the core region increases market prices in hours with high wind availability and price increases in region 1 are higher than in region 2; cf. Figure 5b. Overall,

TABLE 7. Distributional effects of regional compared to supra-regional planning for one bidding zone (in EUR/yr)

	Core region $\{n_1, \ldots, n_4\}$	Region 1 $\{n_5\}$	Region 2 $\{n_6\}$
Renewable cost	-2453		
Network cost	1850		
Consumer rent	3449	129	130
Network rent	0	-255	255
Renewable rent	-2616	-288	-6
Redispatch cost	1409		
Backup cost	0		
Welfare	26	-413	378

the higher renewable rent in region 1 more than compensates other losses compared to region 2 which observes welfare losses.

In case of a single bidding zone, regional planning results in additional wind and less PV capacity as compared to supra-national planning. Regional planning therefore has the opposite effect on investment levels for renewable technologies as in the case with two bidding zones. Wind at n_3 (the cheapest RES technology) which replaces some PV at n_1 which, together with additional network investment, allows for cost savings in the core region of 603 EUR/yr. Additional wind capacity reduces electricity prices in the core region in about 100 hours, see Figure 5a, which increases the consumer rent (+3439 EUR/yr) and decreases the renewable rent (-2616 EUR/yr) more than the renewable cost. The larger amount of wind capacity requires a higher level of redispatch cost, which results in only small welfare gains in the core region.

In both neighboring markets the consumer rent benefits only to a small extent from lower market prices. As lower market prices result from additional wind capacity, they have a negative effect on the renewable rent in region 1 (-288 EUR/yr) but limited effects on the renewable rent in region 2 (-6 EUR/yr). Electricity prices in the core region converge towards prices in region 1 in hours with high wind generation reducing (increasing) the network rent between the core region and region 1 (region 2). This results in overall welfare losses in region 1 and welfare gains in region 2.

In case of nodal pricing, regional planning sees the highest wind investment at n_3 of all scenarios and lowest renewable cost. Compared to supra-regional planning, the regulator plans with two additional lines between the border nodes n_3 and n_4 to integrate the additional wind generation, which re-route physical electricity flows to a certain extend to n_4. Prices increase more at n_3 and n_4 than at n_1 and n_2 in about 250 hours and n_3 experiences 50 additional hours with low electricity prices; cf. Figure 5c. Even though overall investment cost increase in the core region by 1807 EUR/yr, the collection of significant amounts of network rent (3080 EUR/yr) is the main driver for welfare gains. Thus, nodal pricing is the only case that allows welfare gains in the core region for regional planning with losses of consumer rent and renewable rent at the same time.

On a nodal basis, n_3 and n_4 experience the main shift in welfare as a result of replacing PV at n_4 with wind at n_3. At both nodes, the combination of more wind and less PV capacity with additional network investment results in higher prices, lower consumer rent, and an additional network rent. Overall nodal welfare

TABLE 8. Distributional effects of regional compared to supra-regional planning for nodal pricing (in EUR/yr)

	$\{n_1\}$	$\{n_2\}$	$\{n_3\}$	$\{n_4\}$	Core region $\{n_1,\ldots,n_4\}$	Region 1 $\{n_5\}$	Region 2 $\{n_6\}$
Renewable cost	0	0	14 563	-16 556	-1993		
Network cost	0	0	1850	1850	3700		
Consumer rent	-86	201	-186	-453	-524	-535	-717
Network rent	-195	-90	1628	1736	3080	-14	-12
Renewable rent	133	0	13 124	-13 984	-727	290	576
Welfare	-148	111	-1848	2006	122	-259	-153

decreases at n_3 as the additional renewable rent is lower than the renewable cost and it increases at n_4 with lower decreases in renewable rent than renewable cost. For n_1 losses in network rent and consumer rent outweigh additional renewable rent for PV, whereas higher consumer rent at n_2 allows a modest increase in welfare.

Both neighboring markets experience welfare losses as price effects result in higher reductions of consumer rent than increases in renewable rent.

7. DISCUSSION

In this contribution we have extended an existing multilevel electricity market modeling approach to account for the effect of regional planning objectives of the public authority on economic efficiency in an electricity system with coupled regional spot markets. Our analysis adds to a well-established literature on electricity market modeling, which typically does not focus on cross-border trade. Existing contributions either (i) restrict themselves to heuristics to capture cross-border electricity flows, (ii) assume supra-regional objectives of the public authorities, or (iii) simply abstract from neighboring markets. We show that the rigorous analysis of regional objectives in a system of interconnected regional markets has serious implications on the results. In particular, the consideration of regional planning objectives of the regulator yields different investment plans for transmission expansion as well as renewable technology and allocational choices. We show that this is true for a wide range of liberalized electricity markets, i.e., electricity markets with nodal pricing as they are used in parts of the US and also zonal electricity markets as they are used in Europe or Australia. This is an important result, as today's toolboxes for transmission investment planning and for renewable allocation do not address regional motivations convincingly. Since the modeling of national or regional objectives of a regulator implies a high degree of complexity, it is not possible to compute significantly larger instances using the presented approach. However, the model is well suited to illustrate the effects of cross-border aspects using reduced examples.

In order to illustrate our approach, we presented a case study consisting of a core region and two adjacent regions. Regional planning objectives, of course, lead to welfare gains in the core region. We show that adjacent regions may either win or loose. More importantly, we find substantial distributional effects as compared to supra-regional planning. Distributional effects occur within the core region as well as in the adjacent regions. Whereas there is no clear relation between market design and the impact of the planning perspective, we can nevertheless identify drivers of redistribution. In particular, line investment is taken as to integrate more cheap

renewable energy in the core region and to increase network rents from trade with the adjacent regions.

In future work, our model can be applied to more realistic network instances and larger data sets. Computational challenges will then come up that need to be addressed by novel algorithmic developments. Further interesting pathways are the consideration of uncertainty on renewable scenarios in neighboring markets, the analysis of investment in cross-border line capacity, or an assessment of the scope for coordination of renewable targets. It is also a clear challenge to include our approach into a game with several players on the first level for nodal and zonal pricing. This would allow to analyze strategic transmission investment among multiple players. Those questions are left for future research.

Acknowledgments

This research has been performed as part of the Energie Campus Nürnberg (EnCN) and is supported by funding of the Bavarian State Government and by the Emerging Talents Initiative (ETI) of the Friedrich-Alexander-Universität Erlangen-Nürnberg for Jonas Egerer. The authors also thank the Deutsche Forschungsgemeinschaft for their support within projects A05, B08, and B09 in the Sonderforschungsbereich/Transregio 154 "Mathematical Modelling, Simulation and Optimization using the Example of Gas Networks".

References

Ambrosius, M., J. Egerer, V. Grimm, and A. H. v. d. Weijde (2019). "The role of expectations for market design – on structural regulatory uncertainty in electricity markets." In: *EPRG Working Paper* 1915. URL: https://www.eprg.group.cam.ac.uk/eprg-working-paper-1915.

Ambrosius, M., V. Grimm, T. Kleinert, F. Liers, M. Schmidt, and G. Zöttl (2018). *Endogenous Price Zones and Investment Incentives in Electricity Markets: An Application of Multilevel Optimization with Graph Partitioning*. URL: http://www.optimization-online.org/DB_HTML/2018/10/6868.htm.

BMWi - Federal Ministry of Economic Affairs and Energy of Germany (2020). *Action Plan Bidding Zone*. English. URL: https://www.bmwi.de/Redaktion/EN/Downloads/a/action-plan-bidding-zone.html.

Boucher, J. and Y. 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.

Bravo, D., E. Sauma, J. Contreras, S. de la Torre, J. A. Aguado, and D. Pozo (2016). "Impact of network payment schemes on transmission expansion planning with variable renewable generation." In: *Energy Economics* 56, pp. 410–421. DOI: 10.1016/j.eneco.2016.04.006.

Buijs, P. and R. Belmans (2012). "Transmission Investments in a Multilateral Context." In: *IEEE Transactions on Power Systems* 27.1, pp. 475–483. DOI: 10.1109/TPWRS.2011.2162593.

Daxhelet, O. and Y. 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, S., V. Kalashnikov, G. A. Pérez-Valdés, and N. Kalashnykova (2015). *Bilevel Programming Problems*. Springer. DOI: 10.1007/978-3-662-45827-3.

Dennis, J. S., S. G. Kelly, R. R. Nordhaus, and D. W. Smith (2016). *Federal/State Jurisdictional Split: Implications for Emerging Electricity Technologies*. Tech. rep. URL: http://eta-publications.lbl.gov/sites/default/files/lbnl-1006675.pdf.

Egerer, J. and W.-P. Schill (2014). "Power System Transformation toward Renewables: Investment Scenarios for Germany." In: *Economics of Energy & Environmental Policy* 3.2, pp. 29–43. DOI: 10.5547/2160-5890.3.2.jege.

European Commission, Directorate-General for Energy, DNV-GL, ECN, and ECORYS (2014). *Options for future European electricity system operation.* English. URL: http://dx.publications.europa.eu/10.2833/540766.

European Parliament and European Commission (2019). *Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity.* English. URL: http://data.europa.eu/eli/reg/2019/943/oj.

Fischetti, M., I. Ljubić, M. Monaci, and M. Sinnl (2017). "A New General-Purpose Algorithm for Mixed-Integer Bilevel Linear Programs." In: *Operations Research* 65.6, pp. 1615–1637. DOI: 10.1287/opre.2017.1650.

– (2018). "On the use of intersection cuts for bilevel optimization." In: *Mathematical Programming* 172.1-2, pp. 77–103. DOI: 10.1007/s10107-017-1189-5.

– (2019). "Interdiction games and monotonicity, with application to knapsack problems." In: *INFORMS Journal on Computing* 31.2, pp. 390–410. DOI: doi.org/10.1287/ijoc.2018.0831.

Glachant, J.-M. and L. Meeus (Mar. 2018). *Electricity Network Regulation in the EU - the challenges ahead for transmission and distribution.* DOI: 10.4337/9781786436092.

Grimm, V., T. Kleinert, F. Liers, M. Schmidt, and G. Zöttl (2019). "Optimal price zones of electricity markets: a mixed-integer multilevel model and global solution approaches." In: *Optimization Methods and Software* 34.2, pp. 406–436. DOI: 10.1080/10556788.2017.1401069.

Grimm, V., A. Martin, M. Schmidt, M. Weibelzahl, and G. Zöttl (2016). "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, V., L. Schewe, M. Schmidt, and G. 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.

Hansen, P., B. Jaumard, and G. Savard (1992). "New branch-and-bound rules for linear bilevel programming." In: *SIAM Journal on Scientific and Statistical Computing* 13.5, pp. 1194–1217. DOI: 10.1137/0913069.

Holmberg, P. and E. 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.

Huppmann, D. and J. Egerer (2015). "National-strategic investment in European power transmission capacity." In: *European Journal of Operational Research* 247.1, pp. 191–203. DOI: 10.1016/j.ejor.2015.05.056.

Kasina, S. and B. F. Hobbs (Sept. 2020). "The value of cooperation in interregional transmission planning: A noncooperative equilibrium model approach." In: *European Journal of Operational Research* 285.2, pp. 740–752. DOI: 10.1016/j.ejor.2020.02.018.

Kleinert, T., M. Labbé, F. Plein, and M. Schmidt (2020). "There's No Free Lunch: On the Hardness of Choosing a Correct Big-M in Bilevel Optimization." In: *Operations Research.* DOI: 10.1287/opre.2019.1944. online first.

Kleinert, T. and M. Schmidt (2019). "Global Optimization of Multilevel Electricity Market Models Including Network Design and Graph Partitioning." In: *Discrete Optimization* 33, pp. 43–69. DOI: 10.1016/j.disopt.2019.02.002.

Krebs, V., L. Schewe, and M. Schmidt (2018). "Uniqueness and Multiplicity of Market Equilibria on DC Power Flow Networks." In: *European Journal of Operational Research* 271.1, pp. 165–178. DOI: 10.1016/j.ejor.2018.05.016.

Lozano, L. and J. C. Smith (2017). "A value-function-based exact approach for the bilevel mixed-integer programming problem." In: *Operations Research* 65.3, pp. 768–786. DOI: 10.1287/opre.2017.1589.

Mínguez, R. and R. García-Bertrand (2016). "Robust transmission network expansion planning in energy systems: Improving computational performance." In: *European Journal of Operational Research* 248.1, pp. 21–32. DOI: 10.1016/j.ejor.2015.06.068.

Munoz, F., B. Hobbs, and J.-P. Watson (2016). "New bounding and decomposition approaches for MILP investment problems: Multi-area transmission and generation planning under policy constraints." In: *European Journal of Operational Research* 248.3, pp. 888–898. DOI: 10.1016/j.ejor.2015.07.057.

Newbery, D., M. G. Pollitt, R. A. Ritz, and W. Strielkowski (2018). "Market design for a high-renewables European electricity system." In: *Renewable and Sustainable Energy Reviews* 91, pp. 695–707. DOI: 10.1016/j.rser.2018.04.025.

NREL (2018). *Interconnections Seam Study*. Tech. rep. URL: https://www.nrel.gov/analysis/seams.html.

NRRI (2015). *Electric Transmission Seams: A Primer White Paper*. Tech. rep. URL: https://pubs.naruc.org/pub/FA86CD9B-D618-6291-D377-F1EFE9650C73.

O'Neill, R. P., E. A. Krall, K. W. Hedman, and S. S. Oren (2013). "A model and approach to the challenge posed by optimal power systems planning." In: *Mathematical Programming* 140.2, pp. 239–266. DOI: 10.1007/s10107-013-0695-3.

Pineda, S. and J. M. Morales (2019). "Solving Linear Bilevel Problems Using Big-Ms: Not All That Glitters Is Gold." In: *IEEE Transactions on Power Systems* 34.3, pp. 2469–2471. DOI: 10.1109/TPWRS.2019.2892607.

Pozo, D., E. E. Sauma, and J. Contreras (2013). "A Three-Level Static MILP Model for Generation and Transmission Expansion Planning." In: *IEEE Transactions on Power Systems* 28.1, pp. 202–210. DOI: 10.1109/TPWRS.2012.2204073.

Regionales Rechenzentrum Erlangen (2020). *Woodcrest Cluster*. URL: https://www.anleitungen.rrze.fau.de/hpc/woody-cluster/ (visited on 10/01/2020).

Roques, F. and C. Verhaeghe (2016). *Report for ENTSO-E - Options for the Future of Power System Regional Coordination*. Tech. rep. URL: https://docstore.entsoe.eu/Documents/Publications/Position%20papers%20and%20reports/entsoe_fti_161207.pdf.

Sauma, E. E. and S. S. Oren (2006). "Proactive planning and valuation of transmission investments in restructured electricity markets." In: *Journal of Regulatory Economics* 30.3, pp. 358–387. DOI: 10.1007/s11149-006-9012-x.

– (2009). "Do generation firms in restructured electricity markets have incentives to support social-welfare-improving transmission investments." In: *Energy Economics* 31.5, pp. 676–689. DOI: 10.1016/j.eneco.2009.01.015.

Spyrou, E., J. L. Ho, B. F. Hobbs, R. M. Johnson, and J. D. McCalley (2017). "What are the Benefits of Co-Optimizing Transmission and Generation Investment? Eastern Interconnection Case Study." In: *IEEE Transactions on Power Systems* 32.6, pp. 4265–4277. DOI: 10.1109/TPWRS.2017.2660249.

Tahernejad, S., T. K. Ralphs, and S. T. DeNegre (2016). *A branch-and-cut algorithm for mixed integer bilevel linear optimization problems and its implementation*. Tech. rep. COR@L Laboratory Technical Report 16T-015-R3, Lehigh University.

Tohidi, Y. and M. R. Hesamzadeh (2014). "Multi-Regional Transmission Planning as a Non-Cooperative Decision-Making." In: *IEEE Transactions on Power Systems* 29.6, pp. 2662–2671. DOI: 10.1109/TPWRS.2014.2312021.

Tohidi, Y., M. R. Hesamzadeh, and F. Regairaz (2018). "Modified Benders Decomposition for Solving Transmission Investment Game With Risk Measure." In: *IEEE Transactions on Power Systems* 33.2, pp. 1936–1947. DOI: 10.1109/TPWRS.2017.2743823.

Xu, P. and L. Wang (2014). "An exact algorithm for the bilevel mixed integer linear programming problem under three simplifying assumptions." In: *Computers & Operations Research* 41, pp. 309–318. DOI: 10.1016/j.cor.2013.07.016.

Zöttl, G. (2010). "A framework of Peak Load Pricing with strategic firms." In: *Operations Research* 58.6, pp. 1637–1649. DOI: 10.1287/opre.1100.0836.

Appendix A. Notation

Table 9. Technical and economic quantities.

Symbol	Explanation
N	Demand and Generation nodes
N^{core}	Nodes in the core region
N^{sur}	Nodes in the surrounding markets
Z_k	Bidding zone k for $k = 1, \ldots, p$
L	Transmission lines
L^{ex}	Existing transmission lines
L^{new}	Candidate transmission lines
L^{inter}	Inter-zonal transmission lines
L^{core}	Transmission lines within the core region
G_n^{all}	All generation technologies at node n
G_n^{ex}	Existing generation technologies at node n
G_n^{new}	Candidate generation technologies at node n
G_n^{conv}	Conventional generators at node n
G_n^{res}	Renewable generators at node n
G_n^{bu}	Backup generators at node n
T	Time periods
τ_t	Length of time period t
B_l	Susceptance of transmission line $l \in L$
$\bar{f}_l$	Thermal capacity of transmission line $l \in L$
β_l	Inter-zonal transmission capacity factor of line l
$a_{n,t}$	Intercept of the inverse demand function $p_{n,t}$
$b_{n,t}$	Slope of the inverse demand function $p_{n,t}$
c_g^{inv}	Investment costs of generator g
c_g^{var}	Variable costs of production of generator g
$\bar{q}_g^{\text{fix}}$	Fixed capacity of existing generator g
$\bar{q}_g^{\text{max}}$	Maximum capacity that can be installed for candidate generator g
$\bar{q}_g^{\text{mod}}$	Module capacity of renewable generation project g
$\bar{y}_l$	Maximum number of modules of line l
$\bar{x}_g$	Maximum number of modules of renewable project g
$\omega_{g,t}$	Availability factors of generator g in time period t
$d_{n,t}^{\text{ref}}$	Reference demand at node n in time period t
c^{ls}	Load shedding costs
s_n^{cong}	Share of congestion rent at node n
y_l	Number of modules built for line l
x_g	Number of modules built for renewable project g
$\bar{q}_g$	Capacity of candidate generator g
$\pi_{n,t}$	Market price at node n in time period t
$d_{n,t}^{\text{spot}}$	Spot-market demand at node n in time period t
$q_{g,t}^{\text{spot}}$	Spot-market generation of generator g in time period t
$f_{l,t}^{\text{spot}}$	Spot-market power flow on line l at time period t
$d_{n,t}^{\text{red}}$	Demand after redispatch at node n in time period t
$q_{g,t}^{\text{red}}$	Generation after redispatch of generator g in time period t
$f_{l,t}^{\text{red}}$	Power flow after redispatch on line l at time period t
$d_{n,t}^{\text{ls}}$	Load shedding at node n in time period t
$\theta_{n,t}$	Voltage angle at node n in time period t

Appendix B. Benders-like decomposition approach

The Benders master problem used in Algorithm 1 is given by

$$\max \quad \tau - \sum_{n \in N^{\text{core}}} \sum_{g \in G_n^{\text{res}} \cap G_n^{\text{new}}} c_g^{\text{inv}} \bar{q}_g^{\text{mod}} x_g - \sum_{l \in L^{\text{new}}} c_l^{\text{inv}} y_l \tag{32a}$$

$$\text{s.t.} \quad \tau \leq a^\top \begin{pmatrix} x \\ y \end{pmatrix} + b \quad \text{for all } (a,b) \in O, \tag{32b}$$

$$\text{network design: (1)}, \tag{32c}$$

$$\text{renewable energy investment: (2), (3)}, \tag{32d}$$

$$\text{integer-to-binaries: (30), (31)}. \tag{32e}$$

For suitably chosen optimality cuts O, this is a relaxation of the full trilevel problem of Section 2. In particular,

$$\tau \geq \psi_1 + \sum_{n \in N^{\text{core}}} \sum_{g \in G_n^{\text{res}} \cap G_n^{\text{new}}} c_g^{\text{inv}} \bar{q}_g^{\text{mod}} x_g + \sum_{l \in L^{\text{new}}} c_l^{\text{inv}} y_l$$

needs to hold for every set of optimality cuts O. For a fixed solution (x^*, y^*) of the master problem (32), we can solve the second-level and third-level problem subsequently; see Section 4. Afterward, we can evaluate the first-level objective function value $\psi_1^*(x^*, y^*)$. We can then derive optimality cuts that are based on a no-good-cut logic:

$$\begin{aligned} \tau \leq \psi_1^*(x^*, y^*) &+ \sum_{n \in N^{\text{core}}} \sum_{g \in G_n^{\text{res}} \cap G_n^{\text{new}}} c_g^{\text{inv}} \bar{q}_g^{\text{mod}} x_g^* + \sum_{l \in L^{\text{new}}} c_l^{\text{mod}} y_l^* \\ &+ \psi_{\text{ub}}^* \left(\sum_{(l,i): y_{l,i}^{\text{bin}} = 0} y_{l,i}^{\text{bin}} + \sum_{(l,i): y_{l,i}^{\text{bin}} = 1} (1 - y_{l,i}^{\text{bin}}) \right) \\ &+ \psi_{\text{ub}}^* \sum_{n \in N} \left(\sum_{(g,i): x_{g,i}^{\text{bin}} = 0} x_{g,i}^{\text{bin}} + \sum_{(g,i): x_{g,i}^{\text{bin}} = 1} (1 - x_{g,i}^{\text{bin}}) \right). \end{aligned} \tag{33}$$

Furthermore, we can state two additional optimality cuts:

$$\tau \leq \psi_{\text{ub}}^*(\cdot, y^*) + \psi_{\text{ub}}^* \left(\sum_{(l,i): y_{l,i}^{\text{bin}} = 0} y_{l,i}^{\text{bin}} + \sum_{(l,i): y_{l,i}^{\text{bin}} = 1} (1 - y_{l,i}^{\text{bin}}) \right), \tag{34}$$

$$\tau \leq \psi_{\text{ub}}^*(x^*, \cdot) + \psi_{\text{ub}}^* \sum_{n \in N} \left(\sum_{(g,i): x_{g,i}^{\text{bin}} = 0} x_{g,i}^{\text{bin}} + \sum_{(g,i): x_{g,i}^{\text{bin}} = 1} (1 - x_{g,i}^{\text{bin}}) \right). \tag{35}$$

The values of ψ_{ub}^*, $\psi_{\text{ub}}^*(x^*, \cdot)$, and $\psi_{\text{ub}}^*(\cdot, y^*)$ denote upper bounds for the entire trilevel problem, the trilevel problem with fixed renewable project decisions x^*, and with fixed network design decisions y^*, respectively. These bounds can be derived, e.g., by solving a single-level mixed-integer linear program (MILP) that is closely related to the concept of the high-point relaxation of the trilevel problem; see Kleinert and Schmidt (2019).

Appendix C. Time Periods for the Test Case

Table 10. Time periods with season (winter/summer), probability, demand factor, reference price, as well as capacity factors for Wind and PV

	Season	Prob	Demand	Ref price (EUR/MWh)	Wind	PV
t_1	W	0.005	1.0	155	0.66	0.00
t_2	W	0.040	1.0	155	0.20	0.00
t_3	W	0.005	1.0	155	0.02	0.00
t_4	W	0.010	0.9	60	0.66	0.11
t_5	W	0.080	0.9	60	0.20	0.11
t_6	W	0.010	0.9	60	0.02	0.11
t_7	W	0.010	0.8	28	0.66	0.04
t_8	W	0.080	0.8	28	0.20	0.04
t_9	W	0.010	0.8	28	0.02	0.04
t_{10}	W	0.010	0.7	28	0.66	0.00
t_{11}	W	0.080	0.7	28	0.20	0.00
t_{12}	W	0.010	0.7	28	0.02	0.00
t_{13}	W	0.010	0.6	28	0.66	0.00
t_{14}	W	0.080	0.6	28	0.20	0.00
t_{15}	W	0.010	0.6	28	0.02	0.00
t_{16}	W	0.005	0.5	28	0.66	0.00
t_{17}	W	0.040	0.5	28	0.20	0.00
t_{18}	W	0.005	0.5	28	0.02	0.00
t_{19}	S	0.005	0.9	60	0.34	0.58
t_{20}	S	0.040	0.9	60	0.10	0.58
t_{21}	S	0.005	0.9	60	0.01	0.58
t_{22}	S	0.010	0.8	28	0.34	0.45
t_{23}	S	0.080	0.8	28	0.10	0.45
t_{24}	S	0.010	0.8	28	0.01	0.45
t_{25}	S	0.010	0.7	28	0.34	0.32
t_{26}	S	0.080	0.7	28	0.10	0.32
t_{27}	S	0.010	0.7	28	0.01	0.32
t_{28}	S	0.010	0.6	28	0.34	0.10
t_{29}	S	0.080	0.6	28	0.10	0.10
t_{30}	S	0.010	0.6	28	0.01	0.10
t_{31}	S	0.010	0.5	28	0.34	0.00
t_{32}	S	0.080	0.5	28	0.10	0.00
t_{33}	S	0.010	0.5	28	0.01	0.00
t_{34}	S	0.005	0.4	28	0.34	0.00
t_{35}	S	0.040	0.4	28	0.10	0.00
t_{36}	S	0.005	0.4	28	0.01	0.00

(J. Egerer, V. Grimm) (A) Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Economic Theory, Lange Gasse 20, 90403 Nürnberg, Germany; (B) Energie Campus Nürnberg, Fürther Str. 250, 90429 Nürnberg, Germany
Email address: jonas.egerer@fau.de,veronika.grimm@fau.de

(T. Kleinert) (A) Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Discrete Optimization, Cauerstr. 11, 91058 Erlangen, Germany; (B) Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Economic Theory, Lange Gasse 20, 90403 Nürnberg, Germany; (C) Energie Campus Nürnberg, Fürther Str. 250, 90429 Nürnberg, Germany
Email address: thomas.kleinert@fau.de

(M. Schmidt) Trier University, Department of Mathematics, Universitätsring 15, 54296 Trier, Germany
Email address: martin.schmidt@uni-trier.de

(G. Zöttl) (A) Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Industrial Organization and Energy Markets, Lange Gasse 20, 90403 Nürnberg, Germany; (B) Energie Campus Nürnberg, Fürther Str. 250, 90429 Nürnberg, Germany
Email address: gregor.zoettl@fau.de