Evaluation of Risks for Electricity Generation Companies through Reconfiguration of Bidding Zones in Extended Central Western Europe

Tim Felling, Robin Leisen,** Caroline Podewski,* Christoph Weber**

ABSTRACT

In Central Western Europe, a reconfiguration of bidding zones for electricity is frequently discussed as a way to improve congestion management. The current EU guideline on Capacity Allocation and Congestion Management even envisages reviews of the bidding zone configuration (BZC) in regular intervals of three years. Such a change of BZCs gives rise to additional regulatory risk for generation companies. Their expected net present value depends on local prices, which are directly influenced by the BZC. The paper at hand develops a methodology to investigate the impact of this regulatory risk. Therefore the risk of bidding zone changes is modeled using a partly-meshed scenario tree. The risk factors reflected therein are uncertainties in grid developments, in combination with other risks such as changing coal and gas spreads, demand, or renewable infeed variations. Results are compared to the current BZC in Europe and to a nodal setup.

Keywords: Electricity Market Design, Bidding Zone Configuration, Investment Decisions, Risks

https://doi.org/10.5547/01956574.40.SI1.tfel

1. INTRODUCTION

When it comes to pricing in regional electricity markets, economists often refer to so-called nodal pricing as the optimal solution (cf. Schweppe et al., 1988; Hogan, 1992; Bjørndal and Jørnsten, 2001; Ehrenmann and Smeers, 2005; Bjørndal and Jörnsten, 2007). Yet in Central Western Europe (CWE), a zonal pricing framework has been put in place that couples bidding zones[1] whose borders usually align with national borders. Until 2015, a so-called Net Transfer Capacity (NTC) approach was applied, which in 2015 was superseded by Flow-Based Market Coupling (FLB-MC). With FLB-MC, a better representation of physics of the electricity grid is envisaged. However, the approach assumes bidding zones without internal congestions, which appears to be rather impossible at the moment. Redispatch costs and amounts increased significantly over the last years, especially in Germany (BDEW, 2017). This is mainly a consequence of the increasing infeed from renewable energy sources (RES) in combination with the massive delays in grid expansion, but it also reflects changes in regulation, e.g. the nuclear phase-out in Germany.

1. In literature both terms “price zones” and “bidding zones” are used. We use the term “bidding zone” as it is more common in the European regulatory debate.

* House of Energy Markets and Finance, University Duisburg-Essen, Essen, Germany.

** Corresponding author. House of Energy Markets and Finance, University Duisburg-Essen, Essen, Germany. E-mail: robin.leisen@uni-due.de.

The Energy Journal, Vol. 40, SI1. Copyright © 2019 by the IAEE. All rights reserved.

This is why there are broad discussions about the future design of electricity markets in Europe. An optimized bidding zone configuration (BZC) might be one key approach in terms of mid- and long-term redispatch prevention and congestion management. A further split of the German bidding zone—in addition to the split of the former German-Austrian bidding zone into two or more bidding zones within Germany—is frequently discussed, since the massive infeed from northern RES still causes severe internal congestions and loop-flows through neighboring bidding zones.

The current EU guideline on Capacity Allocation and Congestion Management (CACM) even envisages reviews of the BZC in regular intervals of three to five years (cf. Commission Regulation (EU) 2015/1222).[2] Also, internal congestions shall no longer reduce capacities on cross-border lines in order to prevent internal redispatch within countries (bidding zones) (COM (2016) 861 final).[3] Such a change of BZCs gives rise to additional regulatory risk[4] for generation companies (GENCOs). Their expected net present value depends on local prices, which are not only influenced by changes in primary energy and CO_2 certificate prices but also by the BZC. Ergo, a frequent change of BZCs might have a major effect on investment and disinvestment. Various recent analyses have shown that changes in primary energy prices, CO_2 certificate prices, RES expansion, and demand changes have had a major impact on wholesale electricity prices (cf. e.g. Everts, Huber and Blume-Werry, 2016; Kallabis, Pape and Weber, 2016; Bublitz, Keles and Fichtner, 2017; Hirth, 2018). So far, there is little empirical evidence regarding the impact of a reconfiguration of bidding zones, since few reconfigurations have occurred so far in continental Europe. The split of the German-Austrian bidding zone is currently expected to lead to an increase of the average (base) price by 2 EUR/MWh for Austria,[5] i.e. roughly 5% of the current price. Model-based analyses by Blume-Werry, Huber and Everts (2017) have suggested an increase by 1 EUR/MWh. Model-based analyses for other reconfigurations of bidding zones (e.g. Trepper, Bucksteeg and Weber (2015); Egerer, Weibezahn and Hermann (2016); Felling and Weber (2018)) provide mixed evidence: if only large bidding zones are considered, the effects on average prices typically remain limited, whereas with small bidding zones or nodal prices, some areas with high price changes may occur. Moreover, these studies agree that prices tend to decrease in northern Germany, in case Germany is split in several zones.

Hence, the focus of this paper is to quantify the additional regulatory risk induced by a frequent change of bidding zones for GENCOs and investors, taking into account the other risks these stakeholders are facing. The additional risk induced by regulation is also the only one that can be influenced by policy makers. Thus, it needs to be assessed in detail and put into perspective for policy advice. Therefore, we have developed a new methodology that investigates both the BZCs and the risks for GENCOs by computing and assessing the distribution of present values of the contribution margins obtained in future operations. In principle, this methodology is also applicable

2. Notably, a new law in Germany enforces the unified German bidding zone and places an interdiction on TSOs to split up the German bidding zone. However, the law only affects German TSOs and does not apply to decisions affecting the EU.

3. The compromise reached on that point by the end of 2017 foresees, as the preferred solution, an arrangement with fixed free capacities on cross-zonal lines to ensure maximum exchange. A split of price zones is by contrast seen as the "ultima ratio."

4. In the following, the terms risk and uncertainty are used quite interchangeably. We are aware of the strict distinction made by Knight (1921), who defines "risk" as measurable risk with a probability and "uncertainty" as unmeasurable. Since then, others have elaborated further distinctions and other taxonomies (cf. e. g. Renn, Klinke and van Asselt, 2011). Here, we follow what we perceive as a widely used convention in decision theory, which uses "uncertainty" as the broad notion of "absence of certainty" and risk as the subset of decision situations where probabilities may be assigned to different states of the world (cf. also Weber, 2005). In the subsequent quantitative analyses we focus on risk, since modelling "ambiguity" (or "Knightian uncertainty") is challenging and beyond the scope of this paper.

5. According to EEX market data for the front year base product over the period January–May 2018.

All rights reserved. Copyright © 2019 by the IAEE.

to other cases of regulatory (and other) risks that may affect power plant investments in competitive markets, including jurisdictions outside the EU.

The remainder of this article first gives a brief overview of the relevant literature, with a focus on the two streams of "bidding zone configurations" and "investment decisions and risks." Section 3 develops the different steps of the methodology, and section 4 presents the application of the methodology on a grid- and market-model of extended Central Western Europe CWE+ (Austria, Belgium, France, Germany, Luxembourg, Netherlands and Switzerland). Section 5 analyzes the resulting BZCs and the risks for investments in or continued operation of power plants by investigating the uncertainty in present values of the future operation margins. The article ends with a summary of the main findings and outlook on future research.

2. LITERATURE REVIEW

To our knowledge, there are no papers that directly address the question of quantifying regulatory risk for power plant investments in the context of applied regulatory decision-making, such as the definition of bidding zones. Yet a considerable amount of related literature exists that may be broadly divided into the two major streams, "bidding zone configurations" and "investment decisions and risks."

The first stream deals with the ongoing discussion about BZCs in Central Europe. As mentioned earlier, the combination of increasing RES infeed, a delay in grid enforcement, and the current European market design—where bidding zones mostly coincide with national borders, neglecting the physical constraints of the transmission grid—has caused a significant increase in so-called redispatch (BDEW, 2017). The reconfiguration of bidding zones is one approach for mid- and long-term congestion management to reduce redispatch amounts and costs (cf. Commission Regulation (EU) 2015/1222). According to mainstream economic theory, however, the first and best answer to these (and other) congestion management problems is nodal pricing, since nodal prices reflect the marginal generation costs as well as the transmission constraints in the market-clearing algorithm (cf. Schweppe et al., 1988; Hogan, 1992; Ehrenmann and Smeers, 2005; Green, 2007). Nodal pricing is mostly implemented in North American competitive markets, such as PJM Interconnection,[6] where the Independent System Operator (ISO) is responsible for grid operation and power plant scheduling. Yet the implementation of an ISO across Europe is not expected for years to come; hence, a more efficient method of congestion management in Europe will have to rely on zonal pricing, at least in the medium term. In that setting, cluster algorithms are applied in order to identify improved BZCs. Those algorithms cluster the nodes of a system into bidding zones. Although various methods have been used, clustering of locational marginal prices (LMPs) and clustering of power transfer distribution factors (PTDFs) are the two major approaches. Clustering of PTDFs is done, for example, by Kłos et al. (2014) and Kang et al. (2013). Bergh et al. (2016) also cluster PTDFs. They present a case study for CWE and try to quantify the impact of the number of bidding zones on market outcome. The different bidding zones are obtained by clustering nodes with similar nodal PTDF-values for congested lines. Clustering of LMPs has been applied by (amongst others) Imran and Bialek (2007), Burstedde (2012), Wawrzyniak et al. (2013), Breuer, Seeger and Moser (2013) and Breuer and Moser (2014). Burstedde (2012), for example, clusters nodes to zones based on similarity of nodal prices using a hierarchical cluster algorithm following Ward's criterion, whereas Breuer and Moser (2014) apply a genetic algorithm developed in Breuer, Seeger and

6. PJM Interconnection is a regional transmission organization in all or part of thirteen states and the District of Columbia in the north-east of the USA (PJM Interconnection (2018))

Copyright © 2019 by the IAEE. All rights reserved.

Moser (2013) that is based on LMPs to a large-scale model of the European transmission system. They assess the impacts of the optimized bidding zones on operational costs, network security, and market efficiency. Additionally, the authors of this paper have developed an enhanced approach to LMP-based clustering that weights nodes according to their relevance for an electrical network (cf. Felling and Weber, 2016) and which is able to compute robust configurations against a given set of uncertainties (cf. Felling and Weber, 2018).

In contrast to that, there are several studies that evaluate not endogenously determined, but exogenously given bidding zones. Trepper, Bucksteeg and Weber (2015) investigate a split of Germany into two bidding zones and analyze both the occurring price differences and the distributional effects. Egerer, Weibezahn and Hermann (2016) analyze the implications for the German power market if it were to be divided into two or four bidding zones. One of their results is that price differences between zones could be very high, but could occur in a restricted number of hours. They conclude, however, that the results are dependent on the BZC. Blume-Werry, Huber, and Everts (2017) use the fundamental model Green-X in order to analyze the impact of splitting the common German-Austrian bidding zone. One of their key results is that the split has nearly no effects on the security of supply of both countries.

The second relevant literature stream, as mentioned previously, relates to "investment decisions and risks." Practitioners most commonly assess large investment projects based on the net present value, which is determined using the discounted cash flow method (cf. Brealey, Myers and Allen (2017)). But a major shortcoming of this approach is that it neglects optionalities embedded in investment decisions. This approach also uses expected future cash flows to determine whether or not to realize an investment project. Hence, the impact of new information on the course of a project is neglected (cf. Dixit and Pindyck, 1994 and Trigeorgis, 1995). Methods that do take the impact of new information on future decisions into account are commonly labelled as real options approaches. In a narrow interpretation, real options theory is based on the application of principles of the financial options theory. Dixit and Pindyck (1994) and Trigeorgis (1995) not only provide seminal works in that field but are also among the first to present applications of real options theory in the energy and power sector. One key optionality considered there is the flexibility to postpone an investment project. Since then many energy- and power-related applications have been developed. Simultaneously, the term "real option analysis" has been applied in a broader sense, generally encompassing methods that explicitly take into account uncertainties and the future arrival of new information. Fernandes, Cunha and Ferreira (2011), Martínez Ceseña, Mutale and Rivas-Dávalos (2013), Chang (2013), and Kozlova (2017) provide literature reviews of that field. Kozlova (2017) summarizes the uncertainties in renewable energy valuation and concludes that uncertainties regarding regulation are indeed considered, but not as often as other sources of uncertainty such as the electricity price or the fuel price. Examples of researchers that address uncertainties regarding regulation include Laurikka (2006) and Laurikka and Koljonen (2006), who analyze the impact of the EU Emissions Trading System on investments in the Finnish power sector by using the real options approach. Fuss et al. (2008) also analyze investments under climate policy uncertainty. They incorporate the uncertainty regarding the CO_2-price when evaluating an investment in electricity generation projects within the real options framework. A further regulatory uncertainty is the uncertainty regarding support schemes. This is addressed by Boomsma, Meade and Fleten (2012), for example, who adopt in a case study for the Nordic countries the real options approach and analyze the optimal timing of RES investments and the capacity choice under different support schemes. They conclude that feed-in tariffs result in earlier realized projects and renewable energy certificates result in larger projects.

All rights reserved. Copyright © 2019 by the IAEE.

Besides this literature on real options, there are other literature threads that examine investments under uncertainty. Eager, Hobbs and Bialek (2012) notably use a dynamic capacity investment simulation to analyze investments in conventional generation capacity in markets with high penetration of wind. The investment decisions are thereby based on net present value as well as a value-at-risk criterion. Botterud et al. (2001) develop a dynamic simulation model of the Nordic electricity market to analyze investments under uncertainty.

We expand the existing literature by combining these two research streams. At this time, there are no works that specifically analyze the risk of changing BZCs for power plant investors and operators. Therefore, we develop a new methodology for the analysis of the investment in new power plants, and/or the maintenance of existing ones, under different regulatory approaches to BZC.

In order to do so, we have designed a novel approach to assess power plant profitability under uncertainty. We model risk factors with quantifiable probabilities such as input price fluctuations (cf. section 3.2.1), i.e. risk in a narrow sense as in decision theory. We also examine the regulatory risk by considering different regulatory regimes as scenarios. The objective is to apply a theoretically sound method while accounting for the risk aversion of decision makers and considering practically relevant risk factors such as volatile input factor prices, variations in electricity demand and RES infeed, and uncertainties in grid development. While risk factors are hence depicted in an electricity system perspective, their impact on individual investment and operation decisions is described based on the corresponding electricity prices and their uncertainties. These are used as input in a stochastically enhanced discounted cash flow approach. Hence, regulatory uncertainty—with respect to BZC as perceived by GENCOs—is treated as a consequence of the choice of a regulatory regime by policy makers, as well as the response foreseen in the regime to the realizations of risk factors (cf. section 3.2). It is therefore one among several risk factors influencing the profitability and riskiness of power plant investments in competitive markets. We then investigate different schemes of BZCs, including different robust configurations as discussed in Felling and Weber (2018), to describe different regulatory approaches to BZC. By assessing investment profitability and riskiness under these different regulatory settings, we offer new advice to regulatory authorities regarding the impact of different regulatory choices on the energy investment climate.

3. METHODOLOGY

In this section we describe our methodology for the assessment of investment profitability and riskiness under different regulatory settings. In section 3.1, we discuss the general interplay between regulatory decisions and the decisions of GENCOs. Subsequently, we introduce our novel three-step approach that reflects this interplay in section 3.2.

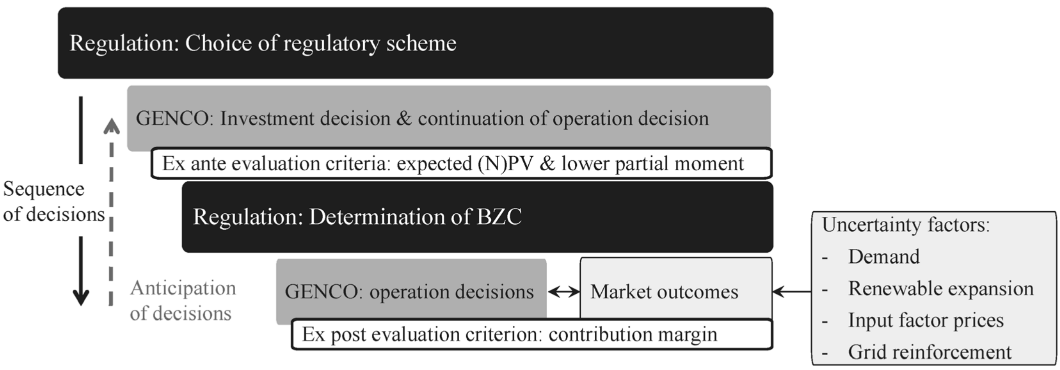
3.1 General Approach

GENCOs, like other firms, will take the existing regulatory framework into account when making their decisions. It is therefore useful to distinguish operational decisions of unit commitment and dispatch from investment (and disinvestment) decisions that typically involve important one-off payments and that induce sunk cost as well as other types of irreversibility. Especially when it comes to such (partially) irreversible decisions, anticipation of possible future developments is a key element of rational decision making. This also includes the anticipation of future regulatory risk, along with other risk factors. This leads us to the lower three levels of decision making sketched in

Copyright © 2019 by the IAEE. All rights reserved.

Figure 1: (1) operation decisions, (2) determination of BZC, and (3) investment and continuation of operation decisions. Decisions made at the upper levels impact subsequent decisions, and conversely, decisions at the lower level have to be anticipated at higher levels. This ought also to be true for the uppermost level, the decision of the regulatory authorities regarding the regulatory scheme for BZCs. This choice of a regulatory scheme determines in particular how often the BZCs are changed in the future and how the BZCs are assessed.[7] Obviously, this decision directly influences the (dis-)investment choices of GENCOs as they decide whether to invest in new power plants or to continue operations of existing ones. At this level, the GENCOs will assess the expected profitability of any (dis-)investment; they will thereby also take its riskiness into account. This requires an anticipation of expected future operational cash flows and their stochastic distribution. These depend on the actual BZCs as they are reconfigured at regular intervals, in our case every five years. Those decisions in turn determine the operational decisions of generators as well as the corresponding market prices, which obviously impact the revenues (represented in our case by the contribution margins) of the GENCOs.

Figure 1: Sequence of decisions and uncertainties



In view of a rational, welfare-maximizing policy choice, the regulator should also anticipate, in his selection of a regulatory scheme, the implications for subsequent decisions; our approach is meant to support the regulatory authorities in their choice. We hence provide decision support to a regulator acting as "benevolent dictator," and disregard any strategic behavior or other deviations from pure (risk-adjusted) welfare maximization.

Therefore, we will evaluate the profitability and riskiness of power plant (dis-)investments from a GENCO perspective under different regulatory schemes. We will use the present value of future cash flows and the lower partial moment as ex ante evaluation criteria (cf. section 3.2.3). In order to evaluate these criteria, not only the determination of BZCs in each base year has to be anticipated, but also the market outcomes depending on various risk factors. Notably, the market outcome influences both the direct operating decisions of GENCOs and the shape of the BZC. Both factors significantly impact the GENCO's operating decisions—hence the contribution margin, which is our ex post evaluation criteria.

Having introduced the general approach of decision making, we introduce in the following section how these sequences of decisions are converted into our developed methodology.

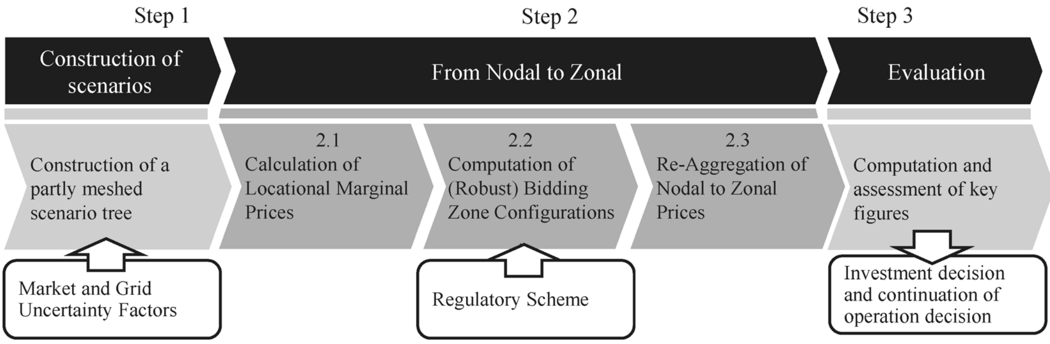
7. We disregard in this paper the possibility of time-inconsistent regulatory choices, i.e. the possibility that a regulator may revise its choice of a regulatory scheme. Obviously this type of regulatory risk is also considered by firms in practice.

All rights reserved. Copyright © 2019 by the IAEE.

3.2 Three-Step Approach

In order to model the previously described interplay of decision making, we have developed a novel three-step approach that allows us to assess the impact of different regulatory schemes for BZC. Figure 2 visualizes the three-step approach:

Figure 2: Three-step approach



First, scenarios are constructed that reflect general market and system uncertainties relevant for electricity market prices. Each scenario describes a possible future market and grid state for a certain year. These are then used to model a meshed scenario tree, with transition probabilities between scenarios of different years. The details of this approach are described in Section 3.2.1. The corresponding parameters for each scenario are then used as input for step 2.

Step 2 comprises the derivation of the new BZCs for a given choice of regulatory scheme. Here three sub-steps are carried out. First we apply a DC optimal power flow (DC-OPF) model (Zimmerman et al., 2011) on a detailed grid model of CWE+ to calculate nodal prices (LMPs) based on the scenario input parameters. Note that the LMPs are independent of the regulatory scheme but depend on the previously defined scenario parameters. In the next sub-step (step 2.2), the calculated LMPs for the different scenarios are then used to cluster the grid nodes into new (robust) BZCs using a hierarchical cluster algorithm (Felling and Weber, 2018). Here, the choice of regulatory scheme determines the way that BZCs are computed, as well as which scenarios are considered simultaneously when determining an optimal or "robust" BZC. The BZCs correspond to an assignment of grid nodes to bidding zones. These are then used in the third sub-step (step 2.3) to re-aggregate the LMPs from sub-step 2.1 to average prices in zones (zonal prices). Finally, in a last step (step 3), we calculate the evaluation criteria to assess the profitability and riskiness of power plant (dis-) investments, i.e. present values of the power plant's contribution margins based on the zonal prices of step 2.3 and the lower partial moment. These key figures provide the basis for the investment and continuation of operation decisions.

In conclusion, the underlying LMPs of step 2.1 of the scenario tree remain unchanged for all different kinds of regulatory choices. The choice of regulatory scheme only determines how and how often the bidding zones are reconfigured and how the LMPs are re-aggregated to zonal prices that are used to determine the contribution margins (CMs).

Ergo, by applying different regulatory schemes on the same scenario tree, the regulatory risks are derived by comparing the investment profitability and riskiness under different schemes.

Copyright © 2019 by the IAEE. All rights reserved.

3.2.1 Construction of Scenarios

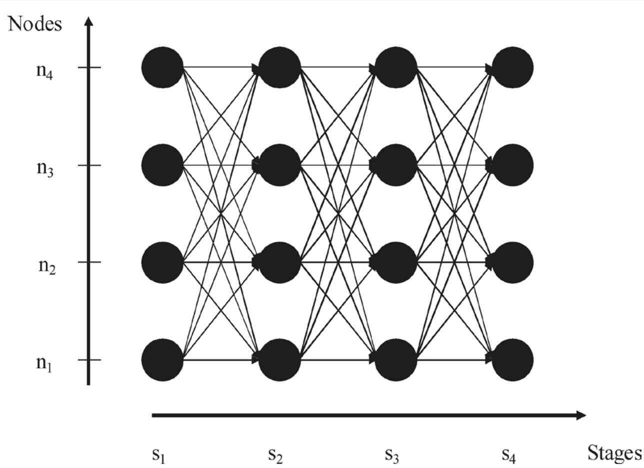
Construction of a Scenario Tree

As mentioned previously, scenarios are constructed first. In order to cope with future uncertainties, it is important to describe them in a parsimonious way while at the same time being as exhaustive as possible. This requires, as a first step, the selection of the key relevant risk factors. As we consider both the regulatory decision on BZCs and the corporate decisions on (dis-) investment, key drivers are those which affect one or both of these decisions. As a BZC in our approach is driven by the LMPs obtained in a DC-OPF, and contribution margins also depend on the (zonal) prices, key drivers in both cases are those that affect prices as well as price patterns. We hence build descriptive scenarios (c.f. Greeuw et al., 2000) which capture key uncertainty factors exogenous to the decision makers. We consequently define as a scenario the combination of a future year and specific realizations for the following four key risk factors (inspired by the findings of Kallabis, Pape and Weber (2016), Hirth (2018) and others):

- RES expansion
- Electricity demand
- Input factor prices, described through the spread between variable costs for coal- vs. gas-fired generation[8]
- (Delays in) Grid expansion

A scenario path is then a sequence of scenarios for the different future years under consideration. In order to derive the distribution of contribution margins and corresponding present values over all possible scenario paths, we define transition probabilities for the shift from one scenario to another between the years. We hence construct a meshed (or recombining) scenario tree, as schematically sketched in Figure 3. The derivation of adequate numerical assumptions is described in the next subsection and in section 4.2.

Figure 3: Construction of a meshed (or recombining) scenario tree



8. The variable costs include the primary energy costs (fuel) as well as the cost of CO_2 emissions induced by CO_2 prices in the European emission certificate trading system.

All rights reserved. Copyright © 2019 by the IAEE.

Derivation of Scenario Parameters

For the derivation of the range of future uncertainties in the key parameters, there are basically two approaches: expert guesses, or extrapolations based on historical statistics.

For the future grid expansion and RES expansion, an extrapolation of historical observations is difficult given the lack of adequate historical observations and/or expected structural changes that invalidate pure extrapolation techniques. Therefore we use official grid development and RES deployment objectives, and estimate possible deviations therefrom (cf. section 4.2).

In contrast, the development of electricity demand is described using historical observations, together with the hypothesis of a simple Brownian Motion for deviations from a longer term trend (see section 4.2).

The input factor price risk is modelled by the uncertainty of the spread between variable costs for coal-fired and gas-fired units. These are currently the marginal (price-setting) technologies for most hours of the year in the European power markets, and this is expected to continue at least for another decade. In that situation also, the contribution margins will be affected mostly by the spread between these two types of variable costs. Notably, the contribution margin of a coal-fired plant depends on the spread between its variable cost and the variable cost of gas-fired generation if the latter sets the power prices. Conversely, gas-fired generation will only earn money during the periods when coal generation sets the price if the spread in variable generation costs has reversed, so that gas is cheaper in terms of variable cost than coal. Again we hypothesize a Geometric Brownian Motion, i.e. independent and normally distributed price increments, in line with standard approaches in finance (cf. e.g. Hull, 2015). We use the approach of Felling and Weber (2018), who also consider the spread between the variable generation costs of gas-fired and coal-fired power plants, to determine the expected average fuel (gas and coal) and CO2 prices for high- and low-spread scenarios, making use of historical observations of the year 2015 to determine the volatility of the spread in the variable cost. This spread is the key price-risk factor, since it includes the combined effects of fuel price and CO_2 price changes.

3.2.2 From Nodal to Zonal Prices

In order to get the zonal prices for each scenario, steps 2.1 through 2.3 are carried out as indicated in Figure 2. At first, LMPs are computed by a DC-OPF using MATPOWER on a high-voltage grid-model of CWE+. For the approximately 2,300 represented nodes, the LMPs are determined for each scenario for the 8,760 hours of a year. The different parameter variations, as described in section 3.2.1, directly influence the LMPs, through (for example) the variation of RES infeed or the status of the network extension.

Second, based on these LMPs, the cluster algorithm is applied in step 2.2 to compute BZCs. Yearly averages of infeed and demand values are then used to compute weights for nodes (cf. Felling and Weber (2016)). The overall objective function for clustering aims at minimizing the price variation within bidding zones. Congested lines, on which ends the prices spread apart, are hence detected and eventually placed between bidding zones.

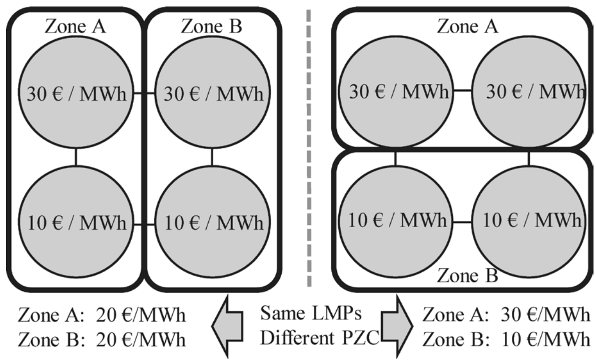
To describe different regulatory settings, we introduce different "regulatory schemes" to determine robust BZCs. A robust BZC is computed by using the LMPs of not one, but several scenarios as input data for the cluster algorithm. Details on this methodology and its benefits are discussed in Felling and Weber (2018). A "regulatory scheme" then determines how many and which scenarios are used to compute the robust configurations. In section 4.3, we introduce four different schemes. For example, the scheme "One robust" assumes that the BZC is determined only once and

Copyright © 2019 by the IAEE. All rights reserved.

is selected in such a way that it is robust against all uncertainties. Therefore the clustering algorithm determines the optimal BZC based on all scenarios, across all parameter variations and base years of the scenario tree. In case of a revision of the BZCs every five years, the scheme "Five Years Robust" computes one BZC for each base year, based on the particular scenarios occurring in that year.

In a last step, the LMPs computed in step 2.1 are re-aggregated to zonal prices according to the previously computed BZCs of the cluster algorithm. As a BZC equals an assignment of each node to a single bidding zone, the average zonal price for each hour can be computed using that assignment. Thus, although the LMPs of each scenario remain the same, different BZCs will eventually result in different zonal prices for the same LMPs. Figure 4 visualizes this effect.

Figure 4: Zonal prices



3.2.3 Assessment of Investment Profitability and Risk

This section describes the evaluation methodology to determine investment profitability and risk and the corresponding two key indicators used: the (expected) present value of contribution margins and the lower partial moments (LPMs).

Computation of the Expected Present Value

The key figure used to evaluate the profitability of power plants is the probability-weighted present value of contribution margins (*wPV*). A comparison of the *wPV* across different regulatory schemes indicates the expected profitability for investments in different locations, as well as the impact of frequent changes of BZCs compared to a conventional, country-based delimitation. We compute the present value of the contribution margins, instead of the net present value (including initial investment expenditures), since we want to consider not only new investments but also the continued operation (vs. early disinvestment) of existing plants.

Therefore, we determine a simplified contribution margin *CM* for every considered power plant *i* and every scenario *s*. The simplification neglects operational restrictions of the power plants and hence assumes that the plants produce electricity whenever the hourly price $P(s,t)$ exceeds the variable costs $VC(s,i)$. The contribution margin also takes into account the annual fixed cost $AFC(i)$ for operating the power plant, notably including costs for insurance, staff, and so on.

$$CM(s,i) = \sum_{t=1}^{8760} max\left(0; P(s,t) - VC(s,i)\right) - AFC(i) \tag{1}$$

Based on (1) we compute the Present Value for a single path *n* by discounting the *CMs* with the discount factor *d(y)*:

All rights reserved. Copyright © 2019 by the IAEE.

$$PV\left(n,i\right)=\sum_{y=1}^{Y}d\left(y\right)\cdot CM\left(s\left(y,n\right),i\right) \tag{2}$$

The $wPV\left(i\right)$ for a power plant i then arises from the discounted *CMs* ($PV(n,i)$) that are weighted with the corresponding probability $p\left(n\right)$ of each path n.

$$wPV\left(i\right)=\sum_{n=1}^{N}p\left(n\right)\cdot PV\left(n,i\right) \tag{3}$$

If this value is negative, it is not economical to continue operation of the respective power plant. For an investment in a new power plant, the investment costs need to be covered as well. In other words, the weighted present value of contribution margins $wPV\left(i\right)$ has to be corrected by the investment cost to obtain the corresponding net present value $NPV\left(i\right)$.[9]

Lower Partial Moments

As a second key indicator, we consider the Lower Partial Moments (LPMs) of order 1 to cope with risk aversion of investors (Fishburn 1977). The LPMs—introduced by Bawa (1975) and Jean (1975)—focus on the downside risk, which is most relevant to investors who want to be aware of risks (Grootveld and Hallerbach 1999). In this paper we use a value of zero as threshold, since it is obviously not profitable to operate a power plant that cannot cover its operation costs. The LMP_1 describes the expected losses (Unser 2000). We calculate the LPM as shown in equation (4).[10]

$$LPM_1^0\left(i\right)=\sum_{n=1}^{N}p\left(n\right)\cdot[\min\left(0,PV\left(n,i\right)-0\right)]^1 \tag{4}$$

Further Evaluations

Additionally, we evaluate the distribution of the *PVs* graphically for selected power plant locations using a box plot. In the box plot, the maximum, 75th percentile, median, 25th percentile, and minimum of the *PVs* are indicated. This illustrates how different regulatory schemes affect the distribution of *PVs*.

On the other hand, we are interested in aggregate assessments of the impact of regulatory schemes on the locational signals provided to GENCOs. These are particularly important for locations with scarce supply. If we consider nodal prices to reflect actual scarcity, the focus of evaluation should be on the locations with the highest *wPVs* in the nodal BZC;[11] we focus in the application on the top 10%. The validity of the locational signals is then measured by the gap between the *wPVs* of those sites with high scarcity and the average *wPVs* of power plants. At the same time, riskiness of investments is evaluated by comparing the average LPMs and standard deviation of *PVs* of the top 10%. We show the standard deviation here in addition to the LPM, since the large proportion of

9. If the planning horizon does not cover the full lifetime of the new power plant, auxiliary assumptions are needed, either to adjust the investment cost or to extrapolate revenues beyond the planning horizon.

10. Note that we use a different sign convention in our definition of the LPM compared to most references (e.g. Fishburn, 1977, Grootveld and Hallerbach, 1999). As defined here, the LPM is always negative, and thus the sign convention is aligned to the sign of the PV, where extreme negative values are less preferred than a value of 0. Furthermore, one may note that Fishburn (1977) and others like Grootveld and Hallerbach (1999) associate the LPM of order 1 with risk-neutral behavior. Yet they use a threshold value that is higher than all realizations of the stochastic variable (here *PV*). This is obviously not the case for our stochastic variable *PV* and the threshold 0. Thus our LPM describes loss aversion, which corresponds to one type of risk aversion.

11. As described later, the nodal BZCs assign each node to a single zone.

Copyright © 2019 by the IAEE. All rights reserved.

negative *PVs* implies that the LPM of order 1 is rather close to the average *wPVs* and hence may not reflect variability of *PVs*.

4. APPLICATION

In this section, we apply the presented methodology to a case study covering CWE+ and different regulatory regimes for obtaining BZCs. The case study covers a period of 20 years in five-year steps, as CACM is most likely to propose a new BZC every (three to) five years. Thus, the four base years in scope are 2020, 2025, 2030 and 2035. Every base year represents five years. 2020 represents the years 2018 to 2022, 2025 represents the period 2023–2027, and so on.

Subsequently, we first summarize the used grid, demand, and RES models in section 4.1. Section 4.2 then presents the used scenarios and parameters. The investigated regulatory schemes are discussed in section 4.3.

4.1 Used Models

The grid model is based on publicly available data (among others, static TSO grid models as under APG (2017); RTE (2017); Tennet (2017)), and comprises the 220 and 380 kV grid. Around 2,300 nodes, 3,600 branches, and 600 transformers are modelled. Phase shifters and HVDC are incorporated into the model as well. HVDC lines are assumed to operate with 5% losses. Envisaged grid extensions are modelled in line with the European Ten-Year-Network-Development-Plan (ENTSO-E (2016)) and the German grid development plan (50Hertz Transmission GmbH et al. (2017)). The status of the grid development, as mentioned in section 3.2.1—in particular, the commissioning and decommissioning dates of both HVDC- and AC-lines and phase shifters—is one key parameter that varies across the scenarios.

Values for residual load, including the infeed of RES, are derived by a separate vertical load model developed in the research group (Osinski and Weber, 2016). In addition, shadow prices for hydropower plants and cross-border flows to non-CWE countries are derived by an initial run of the "Joint Market Model" (JMM) (Meibom et al., 2011; Tuohy et al., 2009) and transferred via an interface to the grid model.

4.2 Scenarios and Input Data

As described in section 3.1, we investigate different scenarios resulting from the combination of different uncertainties. The following section describes the characteristics assumed for the previously introduced parameters.

For the grid expansion, we consider three possible realizations. The first possibility is "realized as planned," so no delay in the grid development is occurring. The second is "delayed by two years", considering a two-year delay on all grid expansion projects, and the third is "delayed by five years", including a five-year delay in comparison to the commissioning date of the German- and European Grid Development Plans (c.f. 50Hertz Transmission GmbH et al., 2017 and ENTSO-E, 2016).

For each of the three other risk factors—"RES expansion," "electricity demand," and "coal-gas spread"—we consider two possible realizations, "high" or "low."

The assumptions regarding the RES expansion are based on the values of the Scenario Outlook & Adequacy Forecast (Scenario B) of the ENTSO-E (2015). The "High" scenario adds +50% to the expected increase in capacities, whereas the "Low" scenario assumes that the RES expansion is slower than expected (-50% of the expected increase).

All rights reserved. Copyright © 2019 by the IAEE.

The values for the electricity demand scenarios are derived from the Brownian motion assumption. A volatility of annual demand of 2% (c.f. Strohbücker, 2011) and uncertainty over five years results in:

$$\text{High:} \quad D_H = D_0 \cdot 1.045 \tag{5}$$

$$\text{Low:} \quad D_L = D_0 \cdot 0.955 \tag{6}$$

It is assumed that there are no increases in (expected) electricity demand during the period 2020–2035.

In line with the methodology sketched in section 3.2.1, we analyze the weekly fuel price changes of the future prices 2018 traded in 2015. We derive therefrom annualized standard deviations for the mean variable costs and for the spread between coal- and gas-fired generation (cf. Felling and Weber (2018)):

$$\text{Mean:} \quad \sigma_{cm} = 0.124 \tag{7}$$

$$\text{Spread:} \quad \sigma_{\Delta c} = 0.067 \tag{8}$$

We use these parameters to derive the values for the "High-" and "Low-" spread scenarios as given in Table 1 for coal, gas, and CO2 prices. The prices for fuel oil and light oil are taken from the world energy outlook (WEO16, New Policies Scenario, International Energy Agency, 2016), and the price for lignite (1.51 €/MWh) from the German grid development plan 2025 (50Hertz Transmission GmbH et al., 2016). Variations in these prices are not considered as they would hardly affect the results, since either variable costs are low (nuclear and lignite plants) or the share in power generation is low (fuel oil and light oil).

Table 1: Fuel prices

		2020		2025		2030		2035	
		high	low	high	low	high	low	high	Low
CO_2	[€/t]	13.34	24.37	19.00	34.73	24.67	45.08	29.01	53.01
Coal	[€/MWh]	6.74	6.96	7.58	7.18	8.42	7.40	8.79	7.19
Gas	[€/MWh]	26.89	16.99	33.27	20.48	39.65	23.97	42.29	24.97
Fuel oil	[€/MWh]	33.50	33.50	40.28	40.28	47.07	47.07	49.83	49.83
Light oil	[€/MWh]	72.07	72.07	86.67	86.67	101.27	101.27	107.20	107.20

For the transition between different grid development stages, we assume the transition probabilities given in the left part of Table 2. The transition probabilities for the other key parameters are indicated in the right part of Table 2.

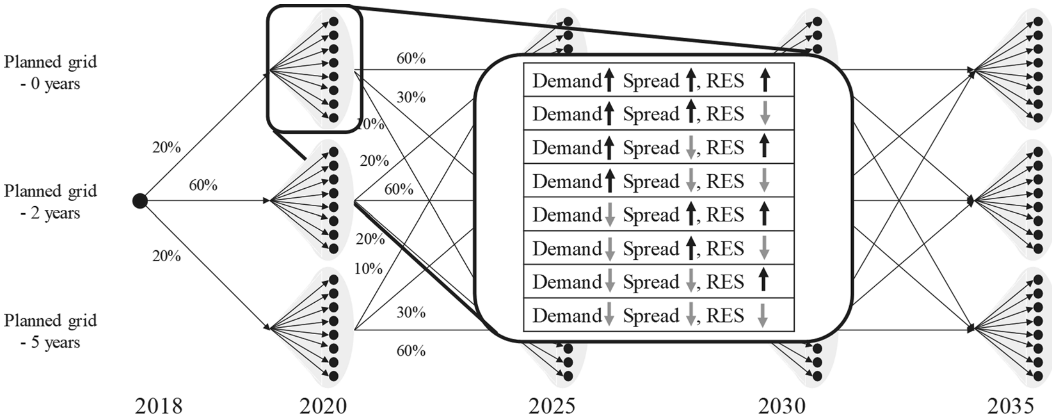
Table 2: Transition probabilities between the grid development scenarios (left) and the other key parameters (right) from one base year to the next.

From→ to	Planned grid -0	Planned grid -2	Planned grid -5	From→ to	High	Low
Planned grid -0	60 %	30 %	10 %	High	75 %	25 %
Planned grid -2	20 %	60 %	20 %	Low	25 %	75 %
Planned grid -5	10 %	30 %	60 %			

This results in a scenario tree consisting of 24 scenarios per base year, i.e. a total of 96 scenarios (see Figure 5).

Copyright © 2019 by the IAEE. All rights reserved.

Figure 5: Constructed partly-meshed scenario tree



4.3 Regulatory Schemes

The aforementioned parameter variations have an impact on the computation of the LMPs in the 96 scenarios in step two. As the nodal prices are the basis for the computation of the BZC in step 2.2 and the re-aggregation to zonal prices in 2.3, they influence both the BZCs and the zonal prices for the later analysis and computation of contribution margins.

Two different schemes to identify robust BZCs are investigated. Moreover, the current BZC in CWE, where national borders align with bidding zone borders, is considered and a pure nodal pricing scheme is also investigated for comparison purposes. Thus, three different so-called "reconfiguration schemes" are evaluated in total.

"Country": No change assumed. Borders of bidding zones still coincide with national borders. One BZC for all scenarios.

"One Robust": Also one BZC for all scenarios. However, the configuration is optimized and derived from the cluster algorithm based on the LMPs of all 96 individual scenarios. The configuration is designed to be robust against all investigated uncertainties. Uncertainty for market participants is thereby reduced by choosing one optimized BZC applicable to all time steps.

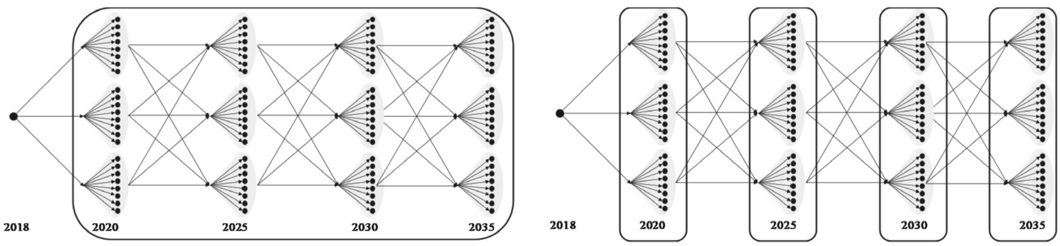
"Five Years Robust": One BZC assumed for every five-year period. This scheme is chosen to align with the CACM regulation that foresees a revision of the BZC every five years. Thus, one optimized BZC is computed for each representative year (2020, 2025, etc.) based on the 24 scenarios of this year. In total, four BZCs therefore occur.

"Nodal": Assumption of nodal prices. With nodal prices, no reconfiguration of bidding zones is necessary. Rather, the asset owners are directly exposed to the nodal price variations. Hence there is one (nodal) BZC under this scheme.

Figure 6 summarizes the two schemes that include endogenous determinations of bidding zones, i.e. the "One Robust" and "Five Years Robust" schemes.

All rights reserved. Copyright © 2019 by the IAEE.

Figure 6: Reconfiguration schemes



"One Robust" **"Five Years Robust"**

5. RESULTS

This section presents key findings obtained from the application of the introduced methodology. Exemplary BZCs are displayed first, in order to provide a glimpse at the effects of different schemes and scenarios with respect to BZCs (see section 5.1). For these, the resulting *wPVs* (see section 5.2) and *LPMs* (see section 5.3) are then compared for power plant locations in CWE+. Subsequently, based on the analyses of the *wPVs*, we select six power plant locations and evaluate the distribution of the *PVs* using box plots (see section 5.4). Furthermore, we evaluate the average of the *wPVs*, the *LPMs*, and the standard deviation of *PVs* for those nodes with highest scarcity (top 10% with highest *wPVs* in the nodal BZC) and compare their results to those for all nodes (see section 5.5).

Table 3 indicates the assumed simplified power plant parameters used for the evaluation. We focus on gas-fired generation, since former analyses indicated that the results for coal-fired power plants are not very sensitive on different schemes for BZC.[12]

Table 3: Power plant parameters

Technology	Efficiency	Investment costs	Operating time	Annual fixed operating costs
	[%]	[€/kW]	[years]	[€/kW]
Coal-fired	46	1400	40	15.06
Gas-fired (Combined Cycle)	60	800	40	6.23

Notes: Based on Sunderkötter and Weber (2012); Steffen and Weber (2013); Konstantin (2017), and our own analysis.

The assumed discount rate is 2%. This reflects an (almost) risk-free discount rate under current central bank policies in Europe. The use of a risk-free discount rate is justified by the fact that the risks of the operation/investment are modelled explicitly outside the discount rate and are captured by other key figures such as LPMs or standard deviations.

5.1 Resulting Robust Bidding Zone Configurations

This section presents the BZCs for different reconfiguration schemes that are assessed by the cluster algorithm to give a glimpse of the shape and size of the optimized BZCs. Given the amount of investigated BZCs, only a few exemplary BZCs are presented here. Those are illustrated in Figure 7.

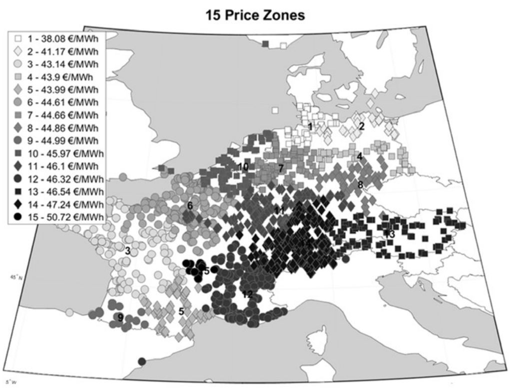
Among the presented BZCs is the configuration of the "One Robust" scheme (top left). In addition, the BZCs for the base years 2020 (top right), 2030 (bottom left), and 2035 (bottom right)

12. The results can be provided upon request.

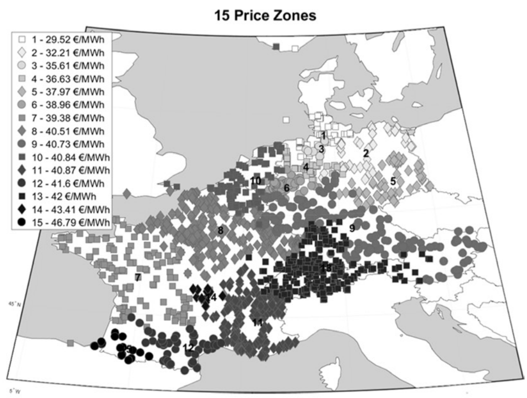
Copyright © 2019 by the IAEE. All rights reserved.

of the “Five Years Robust” scheme are shown. The BZCs obviously differ between the schemes and underlying scenarios; yet, some similarities can be identified. For example, there are always a few rather small zones in northern Germany with low average prices (due to the high amount of infeed from RES). Furthermore, prices in the southern parts of CWE+ are higher than in the northern parts. In contrast, most parts of France show low average prices due to the high share of nuclear power plants. Nevertheless, the shape and size differ across the BZCs. However, with growing grid extension the BZCs seem to stabilize. There are hardly no differences between the “Five Years Robust” configurations in 2030 and 2035.

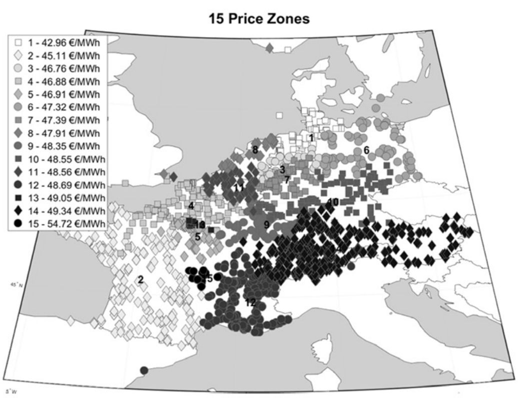
Figure 7: Exemplary BZCs for the different reconfiguration schemes



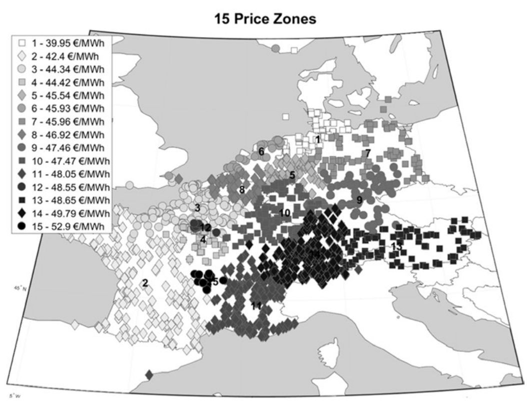
(a) **“One Robust”**—Based on 96 scenarios



“Five Years Robust”—PCZs for the base year 2020 (24 scenarios)



“Five Years Robust”—PCZs for the base year 2030 (24 scenarios)



“Five Years Robust”—PCZs for the base year 2035 (24 scenarios)

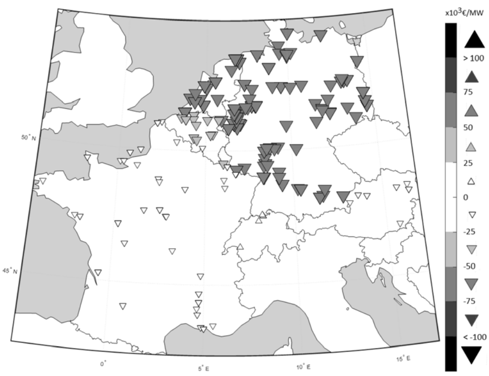
5.2 Resulting Present Values

Figure 8 summarizes the weighted PV of the contribution margins (*wPV*) 0for gas-fired power plants for each configuration scheme. We thereby focus on results in grid locations where thermal power plants are currently installed. The figure on the top left indicates the “Country” scheme as a reference, and the figure on the top right presents the corresponding values in the “Nodal” scheme. The “One Robust” (bottom left) and “Five Years Robust” (bottom right) schemes

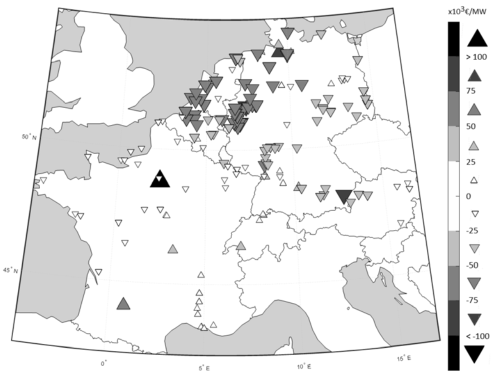
All rights reserved. Copyright © 2019 by the IAEE.

follow. Arrows pointing upwards indicate positive *wPVs*, and arrows pointing downwards indicate negative *wPVs*. Furthermore, the sizes and colors of the arrows indicate to what extent the *wPVs* are positive or negative.

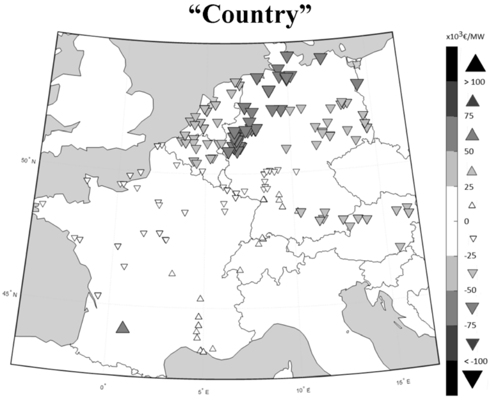
Figure 8: Resulting wPVs (in 10³ €/MW)



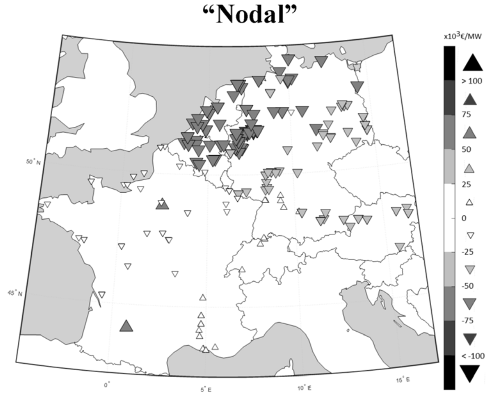
"Country"



"Nodal"



"One Robust"



"Five Years Robust"

The results for gas-fired power plants are diverse; however, a commonality is that the *wPVs* are often negative. The power plants are not able to cover their fixed costs of operation—i.e., even existing power plants do not have sufficient incentives to continue operation. Power plants in northern and western Germany, in particular, cannot operate profitably. In southern and central Germany, *wPVs* vary greatly. Yet, the *wPVs* become positive for some nodes in different schemes. Thereby, differences between nearby nodes also appear, especially for the nodal scheme.

Obviously, the nodal prices depend strongly on the location of the node. Hence, the *wPVs* of the nodal configuration schemes are significantly higher in central and southern Germany, as well as in the south of France, than in the other European regions. The differences between the nodal prices and the other configuration schemes stem from the fact that the prices are not averaged through the construction of zonal respectively country prices. Local congestions directly influence the price at the node.

In general, the choice of the scheme to determine the BZCs has an impact on the *wPVs*. Regional differences in *wPVs* are highest in the "Nodal" scheme and seem to decrease from the "Five Years Robust" scheme to the "One Robust" scheme, e.g. the differences of *wPVs* in the southwest region of Germany (near the border with France) or in northeastern Germany. In order to better un-

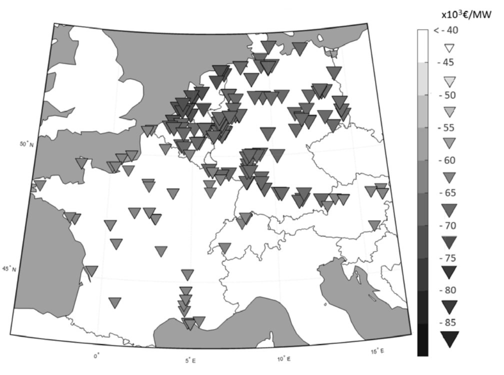
Copyright © 2019 by the IAEE. All rights reserved.

derstand the presented results, section 5.4 shows the distribution of the *wPVs* of all 331,776 paths. Therein we focus on selected nodes in Germany, as they vary the most with changing reconfiguration schemes. Before doing so, we present the corresponding LPMs to the shown nodes in CWE.

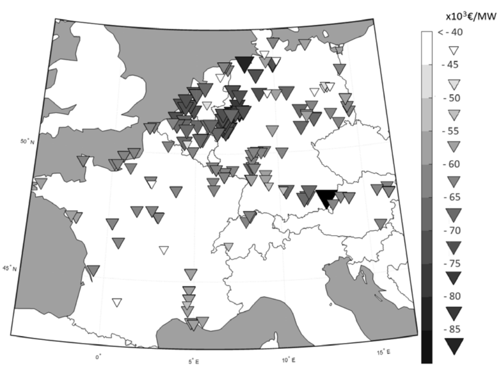
5.3 Resulting LPMs

Figure 9 presents the *LPMs* of gas-fired power plants for the same nodes in each configuration scheme. Again, the figure on the top left indicates the “Country” scheme as a reference, while the figure on the top right gives the corresponding value in the “Nodal” scheme. The “One Robust” (bottom left) and the “Five Years Robust” (bottom right) scheme follow.

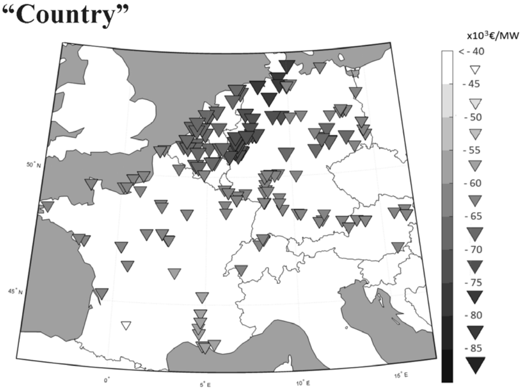
Figure 9: Resulting LPMs (in 10^3 €/MW)



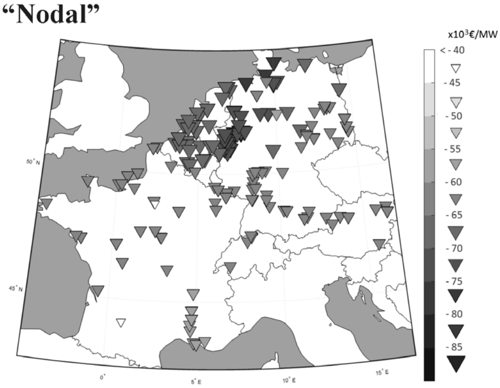
“Country”



“Nodal”



“One Robust”

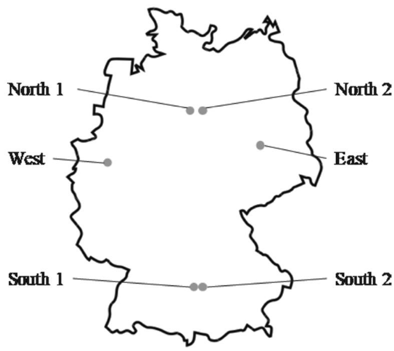


“Five Years Robust”

The LPM is negative by definition (see formula (4)) and describes the expected losses towards the selected threshold of zero. Thus, a LPM close to zero indicates less risk than a more negative LMP. As there are no LPMs with a value of zero, no location is free of risk. Yet, there are nodes with comparably low LPMs. In line with the presented *wPVs* in section 5.2, the height of the LPMs in the nodal scheme vary most between different regions. The south and northeast regions of Germany, in particular show higher regional differences. Again, differences decrease in the “One Robust” and “Five Years Robust” schemes. In contrast to resulting *wPVs*, differences between “One Robust” and “Five Years Robust” are rather low.

All rights reserved. Copyright © 2019 by the IAEE.

Figure 10: Location of analyzed power plant stations

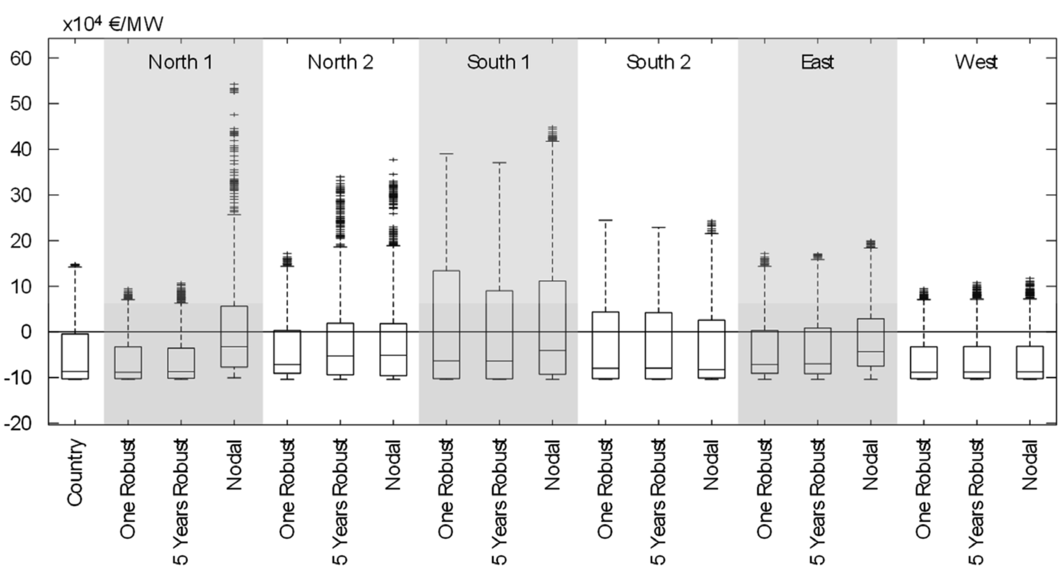


5.4 Resulting Distribution of PVs for Selected Power Plant Locations

The previous two sections provided results for nodes in the entire CWE region. In this section, we focus on regional differences within Germany and show detailed results for selected nodes regarding the impact of different BZCs. Therefore, we show the distributions of the *PVs* over all paths for gas-fired power plants at the selected locations in Germany (see Figure 11). Figure 10 illustrates the locations of the selected nodes, with two in the north, two in the south, one in the west, and one in central Germany, respectively.

Figure 11 presents the box plots of the (probability-weighted) distribution of the *PVs* of all 331,776 paths of the scenario tree. The leftmost bar indicates the distribution of the "Country" scheme as a reference. Subsequently, for all six selected nodes the distributions for the "One Robust," "Five Years Robust," and "Nodal" schemes are presented.

Figure 11: Box plots of *PV* distributions for selected nodes in Germany



In line with the negative *wPVs* presented in section 5.2, the quantiles of the *wPVs* are mostly negative for the location in the west (see Figure 11). In fact, the 75% quantile is always below the profitability threshold of zero. In contrast to that, more than 25% of the *wPVs* in the south

Copyright © 2019 by the IAEE. All rights reserved.

and east German locations are above the threshold, even though the median is always below zero. Yet, this is sufficient for the node “South 1” to achieve a positive *wPV*, as presented previously. Accordingly, the total earnings on the (fewer) lucrative paths exceed the losses of the paths where costs cannot be covered.

Furthermore, the maximal range between losses and profits at each node occurs always in the ”Nodal” scheme, where the profits in particular rise significantly higher than in other schemes. In the other schemes, the range tends to get smaller from the “One Robust” scheme to the “Five Years Robust” scheme. Yet, there is no general rule to be observed. In the south, for example, the range between profits and losses is smaller in the “Five Years Robust” scheme in contrast to the other nodes. Notably, even though nodes are located in the same region and are close to each other, their chance of profits are significantly different even in the robust schemes. Both node pairs in the south and north are frequently at the borders of bidding zones, as visualized in Figure 7.

In general, the performance of gas-fired power plants in the south is better than in the north. Hence, a change of BZCs or even a “Nodal” set-up leads to more chances for gas-fired power plants to earn profits. However, the range of possible outcomes rises significantly, whereas the number of profitable paths mostly increases. Again, there are exceptions, namely the nodes “East” and “North 1,” where the range between profits and losses decreases in the robust schemes in comparison to the country configuration. That applies to the total range but also to the range between the 25% and 75% quantiles.

As expected, changes in the BZC are most beneficial to power plants in the south. Clear differences between the regulatory schemes may be observed, yet no general rule can be derived in terms of which scheme leads to the lowest risk for GENCOs.

5.5 Assessments of the Impact of Regulatory Schemes on the Locational Signals Provided to GENCOs

In this section we analyze the average of the *wPVs* , the *LPMs*, and the standard deviation of *PVs* for those nodes with highest scarcity (top 10% with highest *wPVs* in the nodal BZC), and compare their results to those for all nodes in order to assess the impact of regulatory schemes on the locational signals (cf. Table 4):

Table 4: Average of the *wPVs*, the *LPMs*, and the standard deviation of *PVs*

[€/MW]		Country	One Robust	Five Years Robust	Nodal
Top 10%	*wPV*	-20.370	-2.337	1.953	38.166
	LPM	-59.910	-56.526	-54.272	-42.575
	stdDev(*PV*)	107.506	125.699	127.585	154.518
All nodes	*wPV*	-35.056	-32.204	-31.750	-26.631
	LPM	-61.762	-60.809	-60.488	-57.995
	stdDev(*PV*)	87.812	88.761	88.779	90.613

As described above, the strength of the locational signals is assessed based on the gap between the wPVs of the top 10% nodes and the average wPVs of all power plant nodes. Therefore, the average wPVs for all nodes only change slightly between the different regulatory schemes. By contrast, the results for the top 10% considerably improve and even change sign when moving from the current country-based bidding zones to the nodal BZC. The incentives provided by the two robust schemes are located in between. Hence the “Nodal” scheme provides the best locational signal and notably makes the continued operation of gas-fired power plants in the top 10% locations profitable.

All rights reserved. Copyright © 2019 by the IAEE.

In terms of *LPMs,* the difference between the schemes are more limited. "Nodal" again performs best, but the improvement (increase in *LPM)* for the top 10% is rather small. If we alternatively consider the standard deviation of *PVs* as measure of risk, the results flip: the "Nodal" scheme turns out to be most risky, with an increase in risk of almost 50% as compared to the "Country" scheme. The two robust schemes perform similarly, and are roughly halfway between the two extreme configuration schemes.

The different results regarding the risk under the "Nodal" scheme look puzzling at first sight. Yet they are attributable to the fact that *LPM* focuses on downside risk, whereas the standard deviation is a symmetric measure risk. If the *LPM* improves while the standard deviation deteriorates, this indicates that the possible downsides are reduced while potential upsides increase (scenario paths with high prices). Hence, as a bottom line, standard deviation reflects the common perceptions of nodal prices as being more volatile. But in terms of actual corporate (downside) risk, the *LPMs* provide a more accurate measure. Accordingly, the nodal BZC is to some extent risk-reducing for the critical top 10%.

6. CONCLUSION

In research, both the investment and the disinvestment decisions for power plants and the identification of new BZCs have been addressed repeatedly. Yet the combination of both has not been investigated so far, especially in relation to the European guideline that BZCs are to be adjusted at regular intervals. This paper develops a novel methodology in order to quantify the risk impact of such regulations and to compare the overall riskiness of power plant investments under such regulatory schemes. Hence the implications that go along with a frequent reconfiguration of bidding zones are investigated in a comprehensive setting.

The novel methodology takes several risk factors into account and combines them into scenarios for each computation year. Those in turn are combined with scenario paths in a meshed scenario tree. For each scenario, nodal prices (LMPs) are computed and aggregated to zonal prices based on the particular BZC. Besides the current BZC in CWE+, various new configurations are investigated making use of a cluster algorithm based on the LMPs. As key figures to evaluate the profitability of power plants, the probability-weighted present value of contribution margins (*wPV*) and the corresponding lower partial moments (*LPM*) are assessed. A comparison of the key indicators across different regulatory schemes, and with the "Country" and "Nodal" schemes as reference cases, indicates the impact on profitability and riskiness of (repeated and/or robust) bidding zone reconfigurations.

The riskiness is found to depend strongly on the location of the power plant and its type. Coal-fired power plants always expect positive contribution margins in contrast to gas-fired power plants, which is why we put the focus on the results of gas-fired plants. This reflects the current electricity market situation in CWE, with overcapacities and low CO_2 certificate prices, which according to our computations is likely to last even in future years. But it might also be partially related to an overestimation of the production from coal-fired power plants, as their operational restrictions are not considered in this simplified modelling approach. Conversely, this may also lead to an underestimation of the production of gas-fired power plants. However, we do not expect that this has a significant impact on the results. Another simplification of our approach is the exogenous specification of the power plant park. An endogenous treatment of the evolution of the power plant park would be desirable, yet is left for further research since it adds a further layer of complexity. It would require the solution of a stochastic multi-stage investment equilibrium. The results of such an

Copyright © 2019 by the IAEE. All rights reserved.

exercise would be quantitatively different, but we do not expect major qualitative changes since the stochastic drivers and the resulting regulatory risk remain unchanged.

According to our findings, the chosen regulatory scheme influences the results, although the relationship between any regulatory scheme and the riskiness for GENCOs turns out to be strongly nonlinear. The effect on power plants differs, depending on their location and their assignment to optimized (robust) bidding zones. A change of bidding zones might notably set stronger incentives for power plants in southern Germany. Further research may therefore investigate in depth the risks related to different configuration schemes and the potential benefits of "robustifying" the BZC against various risk factors. An assessment of future changes in the wPVs may also be investigated, as we only consider the PVs for our reference year 2018. There might be incentives to invest in the future due to developments in the years after 2035 that we have not considered.

ACKNOWLEDGMENTS

This research has been partly funded by the Federal Ministry of Economics and Technology (BMWi) of Germany within the framework of the project "Instrumentendesign unter Unsicherheit und nachfrageseitige Flexibilitätsoptionen in Energie-Sektor-Modellen" (project number 0325703).

REFERENCES

50Hertz Transmission GmbH, Amprion GmbH, TenneT TSO GmbH, and TransnetBW GmbH (2016). Netzentwicklungsplan Strom 2025, Version 2015, Zweiter Entwurf Der Übertragungsnetzbetreiber.

——— (2017). Netzentwicklungsplan Strom 2030, Version 2017, Zweiter Entwurf Der Übertragungsnetzbetreiber.

APG (2017). APG Statisches Netzmodell.

Bawa, V.S. (1975). "Optimal Rules for Ordering Uncertain Prospects." *Journal of Financial Economics* 2(1): 95–121. https://doi.org/10.1016/0304-405X(75)90025-2.

BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. (2017). Redispatch in Deutschland.

Bergh, K. Van Den, C. Wijsen, E. Delarue, W. D'haeseleer (2016). "The Impact of Bidding Zone Configurations on Electricity Market Outcomes." Energy Conference 2016, IEEE. https://doi.org/10.1109/ENERGYCON.2016. 7514031.

Bjørndal, M., and K. Jørnsten (2001). "Zonal Pricing in a Deregulated Electricity Market." *The Energy Journal* 22(1): 51–73. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol22-No1-3.

Bjørndal, M., and K. Jørnsten (2007). "Benefits from Coordinating Congestion Management—The Nordic Power Market." *Energy Policy* 35(3): 1978–91. https://doi.org/10.1016/J.ENPOL.2006.06.014.

Blume-Werry, E., C. Huber, and M. Everts (2017). "Splitting Price Zones: The Impact of the German-Austrian Breakup on European Energy Objectives." *European Energy Journal* 6(4): 46–60.

Boomsma, T.K., N. Meade, and S.-E. Fleten (2012). "Renewable Energy Investments under Different Support Schemes: A Real Options Approach." *European Journal of Operational Research* 220(1): 225–37. https://doi.org/10.1016/J.EJOR.2012.01.017.

Botterud, A., M. Korpås, K.-O. Vogstad, and I. Wangensteen (2001). "A Dynamic Simulation Model for Long-Term Analysis of the Power Market." 14th Power Systems Computation Conference (PSCC). http://pscc.ee.ethz.ch/ uploads/tx_ethpublications/s12p04.pdf.

Brealey, R.A., S.C. Myers, and F. Allen (2017). *Principles of Corporate Finance* (twelfth ed.). New York, NY: McGraw-Hill Education.

Breuer, C., N. Seeger, and A. Moser (2013). "Determination of Alternative Bidding Areas Based on a Full Nodal Pricing Approach." *2013 IEEE Power & Energy Society General Meeting*, 1–5. IEEE. https://doi.org/10.1109/ PESMG.2013.6672466.

Breuer, C., and A. Moser (2014). "Optimized Bidding Area Delimitations and Their Impact on Electricity Markets and Congestion Management." *11th International Conference on the European Energy Market (EEM14)*, 1–5. IEEE. https://doi.org/10.1109/EEM.2014.6861218.

Bublitz, A., D. Keles, and W. Fichtner (2017). "An Analysis of the Decline of Electricity Spot Prices in Europe: Who Is to Blame?" *Energy Policy* 107(August): 323–36. https://doi.org/10.1016/J.ENPOL.2017.04.034.

All rights reserved. Copyright © 2019 by the IAEE.

Burstedde, B. (2012). “From Nodal to Zonal Pricing: A Bottom-up Approach to the Second-Best.” *2012 9th International Conference on the European Energy Market*, 1–8. IEEE. https://doi.org/10.1109/EEM.2012.6254665.

Chang, C.-Y. (2013). “A Critical Analysis of Recent Advances in the Techniques for the Evaluation of Renewable Energy Projects.” *International Journal of Project Management* 31(7): 1057–67. https://doi.org/10.1016/j.ijproman.2013. 03.001.

COM (2016) 861 final. 2016. Regulation of the European Parliament and of the Council on the Internal Market for Electricity. *2016/0379(COD)*.

Commission Regulation (EU) 2015/1222. 2015. “COMMISSION REGULATION (EU) 2015/1222 of 24 July 2015 Establishing a Guideline on Capacity Allocation and Congestion Management.” *Official Journal of the European Union L 197* 58(July):24–72. http://data.europa.eu/eli/reg/2015/1222/oj.

Dixit, A.K., and R.S. Pindyck (1994). *Investment under Uncertainty*. Princeton: Princeton University Press.

Eager, D., B.F. Hobbs, and J.W. Bialek (2012). “Dynamic Modeling of Thermal Generation Capacity Investment: Application to Markets with High Wind Penetration.” *IEEE Transactions on Power Systems* 27(4): 2127–37. https://doi.org/10.1109/TPWRS.2012.2190430.

Egerer, J., J. Weibezahn, and H. Hermann (2016). “Two Price Zones for the German Electricity Market—Market Implications and Distributional Effects.” *Energy Economics* 59(September): 365–81. https://doi.org/10.1016/J. ENECO.2016.08.002.

Ehrenmann, A., and Y. Smeers (2005). “Inefficiencies in European Congestion Management Proposals.” *Utilities Policy* 13(2): 135–52. https://doi.org/10.1016/J.JUP.2004.12.007.

ENTSO-E (2015). Scenario Outlook & Adequacy Forecast.

——— (2016). Ten-Year Network Development Plan 2016.

Everts, M., C. Huber, and E. Blume-Werry (2016). “Politics vs Markets: How German Power Prices Hit the Floor.” *The Journal of World Energy Law & Business* 9(2): 116–23. https://doi.org/10.1093/jwelb/jww005.

Felling, T., and C. Weber (2016). “Identifying Price Zones Using Nodal Prices and Supply & Demand Weighted Nodes.” *2016 IEEE International Energy Conference, ENERGYCON 2016*. https://doi.org/10.1109/ENERGYCON.2016. 7514113.

——— (2018). “Consistent and robust delimitation of price zones under uncertainty with an application to Central Western Europe.” *Energy Economics* 75(September): 583–601. https://doi.org/10.1016/j.eneco.2018.09.012.

Fernandes, B., J. Cunha, and P. Ferreira (2011). “The Use of Real Options Approach in Energy Sector Investments.” *Renewable and Sustainable Energy Reviews* 15(9): 4491–97. https://doi.org/10.1016/j.rser.2011.07.102.

Fishburn, P.C. (1977). “Mean-Risk Analysis with Risk Associated with Below-Target Returns.” *The American Economic Review* 67(2): 116–26. http://www.jstor.org/stable/1807225.

Fuss, S., J. Szolgayova, M. Obersteiner, and M. Gusti (2008). “Investment under Market and Climate Policy Uncertainty.” *Applied Energy* 85(8): 708–21. https://doi.org/10.1016/j.apenergy.2008.01.005.

Green, R. (2007). “Nodal Pricing of Electricity: How Much Does It Cost to Get It Wrong?” *Journal of Regulatory Economics* 31(2): 125–49. https://doi.org/10.1007/s11149-006-9019-3.

Greeuw, S.C.H., M.B.A. van Asselt, J. Grosskurth, C.A.M.H. Storms, N. Rijkens-Klomp, D.S. Rothman, and J. Rotmans (2000). *Cloudy Crystal Balls*. Denmark: European Environment Agency.

Grootveld, H., and W. Hallerbach (1999). “Variance vs Downside Risk: Is There Really That Much Difference?” *European Journal of Operational Research* 114(2): 304–19. https://doi.org/10.1016/S0377-2217(98)00258-6.

Hirth, L. (2018). “What Caused the Drop in European Electricity Prices? A Factor Decomposition Analysis.” *The Energy Journal* 39: 143–57. https://doi.org/10.5547/01956574.39.1.lhir.

Hogan, W.W. (1992). “Contract Networks for Electric Power Transmission.” *Journal of Regulatory Economics* 4(3): 211–42. https://doi.org/10.1007/BF00133621.

Hull, J.C. (2015). *Optionen, Futures Und Andere Derivate*. Pearson Studium.

Imran, M., and J.W. Bialek (2007). “Effectiveness of Zonal Pricing Congestion Management Scheme in the European Electricity Market.” *2007 IEEE Power Engineering Society Conference and Exposition in Africa—PowerAfrica*, 1–8. IEEE. https://doi.org/10.1109/PESAFR.2007.4498071.

International Energy Agency (2016). World Energy Outlook 2016. https://doi.org/10.1787/20725302.

Jean, W.H. (1975). “Comparison of Moment and Stochastic Dominance Ranking Methods.” *The Journal of Financial and Quantitative Analysis* 10(1): 151–61. http://www.jstor.org/stable/2330323.

Kallabis, T., C., and C. Weber (2016). “The Plunge in German Electricity Futures Prices—Analysis Using a Parsimonious Fundamental Model.” *Energy Policy* 95: 280–90. https://doi.org/10.1016/j.enpol.2016.04.025.

Kang, C.Q., Q.X. Chen, W.M. Lin, Y.R. Hong, Q. Xia, Z.X. Chen, Y. Wu, and J.B. Xin (2013). “Zonal Marginal Pricing Approach Based on Sequential Network Partition and Congestion Contribution Identification.” *International Journal of Electrical Power & Energy Systems* 51(October): 321–28. https://doi.org/10.1016/J.IJEPES.2013.02.033.

Copyright © 2019 by the IAEE. All rights reserved.

Kłos, M., K. Wawrzyniak, M. Jakubek, and G. Oryńczak (2014). "The Scheme of a Novel Methodology for Zonal Division Based on Power Transfer Distribution Factors." *IECON 2014—40th Annual Conference of the IEEE Industrial Electronics Society*, 3598–3604. https://doi.org/10.1109/IECON.2014.7049033.

Knight, F. (1921). *Risk, Uncertainty, and Profit*. *The Economic Nature of the Firm: A Reader, Third Edition*. Boston: Houghton Mifflin Company. https://doi.org/10.1017/CBO9780511817410.005.

Konstantin, P. (2017). *Praxisbuch Energiewirtschaft Energieumwandlung, -Transport Und -Beschaffung, Übertragungsnetzausbau Und Kernenergieausstieg*. Springer Vieweg.

Kozlova, M. (2017). "Real Option Valuation in Renewable Energy Literature: Research Focus, Trends and Design." *Renewable and Sustainable Energy Reviews* 80(May): 180–96. https://doi.org/10.1016/j.rser.2017.05.166.

Laurikka, H. (2006). "The Impact of Climate Policy on Heat and Power Capacity Investment Decisions." *Emissions Trading and Business*, edited by R. Antes, B. Hansjürgens, and P. Letmathe, 133–49. Heidelberg: Physica-Verlag HD. https://doi.org/10.1007/3-7908-1748-1_10.

Laurikka, H., and T. Koljonen (2006). "Emissions Trading and Investment Decisions in the Power Sector—a Case Study in Finland." *Energy Policy* 34(9): 1063–74. https://doi.org/10.1016/j.enpol.2004.09.004.

Martínez Ceseña, E.A., J. Mutale, and F. Rivas-Dávalos (2013). "Real Options Theory Applied to Electricity Generation Projects: A Review." *Renewable and Sustainable Energy Reviews* 19: 573–81. https://doi.org/10.1016/j.rser.2012. 11.059.

Meibom, P., R. Barth, B. Hasche, H. Brand, C. Weber, and M. O'Malley (2011). "Stochastic Optimization Model to Study the Operational Impacts of High Wind Penetrations in Ireland." *IEEE Transactions on Power Systems* 26 (3): 1367–79. https://doi.org/10.1109/TPWRS.2010.2070848.

Osinski, P., and C. Weber (2016). "Regional Modelling of Electric Load and Renewable Infeed Time Series in Europe." Lissabon, SDEWES Conference 2016.

PJM Interconnection (2018). PJM 2018.

Renn, O., A. Klinke, and M. van Asselt (2011). "Coping with Complexity, Uncertainty and Ambiguity in Risk Governance: A Synthesis." *Ambio* 40(2): 231–46. https://doi.org/10.1007/S13280-010-0134-0.

RTE (2017). RTE Static Grid Model.

Schweppe, F.C., M.C. Caraminis, R.O. Tabors, and R.E. Bohn (1988). "Spot Pricing of Electricity." Kluwer Academic Publishers, Norwell, MA. https://doi.org/10.1007/978-1-4613-1683-1.

Steffen, B., and C. Weber (2013). "Efficient Storage Capacity in Power Systems with Thermal and Renewable Generation." *Energy Economics* 36: 556–67. https://doi.org/10.1016/j.eneco.2012.11.007.

Strohbücker, S. (2011). *Bepreisen von Preis- Und Mengenrisiken Der Strombeschaffung Unter Berücksichtigung von Portfolioaspekten Bei Großkunden Im Strommarkt*. Wiesbaden: Gabler. https://doi.org/10.1007/978-3-8349-6768-8.

Sunderkötter, M., and C. Weber (2012). "Valuing Fuel Diversification in Power Generation Capacity Planning." *Energy Economics* 34(5): 1664–74. https://doi.org/10.1016/j.eneco.2012.02.003.

Tennet (2017). Tennet Statisches Netzmodell.

Trepper, K., M. Bucksteeg, and C. Weber (2015). "Market Splitting in Germany—New Evidence from a Three-Stage Numerical Model of Europe." *Energy Policy* 87: 199–215. https://doi.org/10.1016/j.enpol.2015.08.016.

Trigeorgis, L. (1995). *Real Options in Capital Investment: Models, Strategies, and Applications*. Westport, CT: Greenwood Publishing Group.

Tuohy, A., P. Meibom, E. Denny, and M. O'Malley (2009). "Unit Commitment for Systems With Significant Wind Penetration." *IEEE Transactions on Power Systems* 24(2): 592–601. https://doi.org/10.1109/TPWRS.2009.2016470.

Unser, M. (2000). "Lower Partial Moments as Measures of Perceived Risk: An Experimental Study." *Journal of Economic Psychology* 21(3): 253–80. https://doi.org/10.1016/S0167-4870(00)00004-0.

Wawrzyniak, K., G. Orynczak, M. Klos, A. Goska, and M. Jakubek (2013). "Division of the Energy Market into Zones in Variable Weather Conditions Using Locational Marginal Prices." *IECON 2013—39th Annual Conference of the IEEE Industrial Electronics Society*, 2027–32. IEEE. https://doi.org/10.1109/IECON.2013.6699443.

Weber, C. (2005). *Uncertainty in the Electric Power Industry: Methods and Models for Decision Support*. New York: Springer.

Zimmerman, R.D., C.E. Murillo-Sánchez, R.J. Thomas (2011). "MATPOWER: Steady-State Operations, Systems Research and Education." *Power* Systems 26(1): 12–19. https://doi.org/10.1109/TPWRS.2010.2051168.

All rights reserved. Copyright © 2019 by the IAEE.