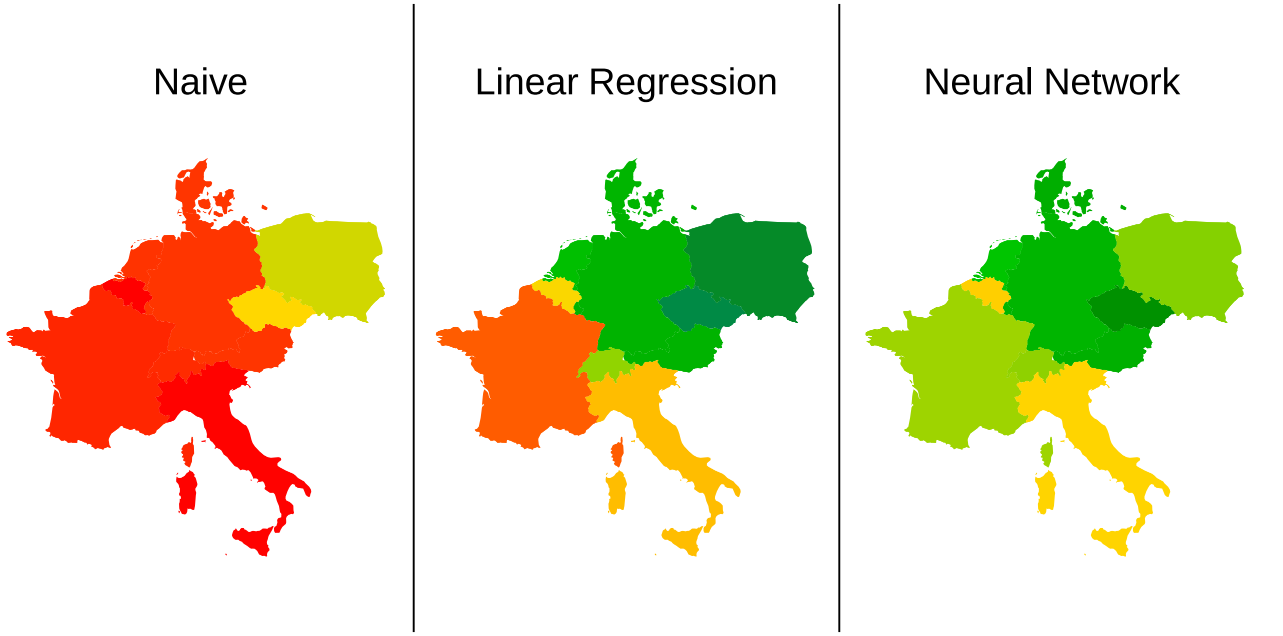
Karlsruhe Institute of Technology

The Merge of Two Worlds: Integrating Artificial Neural Networks into Agent-Based Electricity Market Simulation

By Christoph Fraunholz, Emil Kraft, Dogan Keles, Wolf Fichtner

No. 45 | JULY 2020

WORKING PAPER SERIES IN PRODUCTION AND ENERGY



The Merge of Two Worlds: Integrating Artificial Neural Networks into Agent-Based Electricity Market Simulation

Christoph Fraunholz*, Emil Kraft, Dogan Keles, Wolf Fichtner

Chair of Energy Economics, Institute for Industrial Production (IIP),
Karlsruhe Institute for Technology (KIT),
Hertzstr. 16, 76187 Karlsruhe, Germany

*Corresponding author, email address: christoph.fraunholz@kit.edu,
tel.: +49 721 608-44668

Machine learning and agent-based modeling are two popular tools in energy research. In this article, we propose an innovative methodology that combines these methods. For this purpose, we develop an electricity price forecasting technique using artificial neural networks and integrate the novel approach into the established agent-based electricity market simulation model PowerACE. In a case study covering ten interconnected European countries and a time horizon from 2020 until 2050 at hourly resolution, we benchmark the new forecasting approach against a simpler linear regression model as well as a naive forecast. Contrary to most of the related literature, we also evaluate the statistical significance of the superiority of one approach over another by conducting Diebold-Mariano hypothesis tests. Our major results can be summarized as follows. Firstly, in contrast to real-world electricity price forecasts, we find the naive approach to perform very poorly when deployed model-endogenously. Secondly, although the linear regression performs reasonably well, it is outperformed by the neural network approach. Thirdly, the use of an additional classifier for outlier handling substantially improves the forecasting accuracy, particularly for the linear regression approach. Finally, the choice of the model-endogenous forecasting method has a clear impact on simulated electricity prices. This latter finding is particularly crucial since these prices are a major results of electricity market models.

The Merge of Two Worlds: Integrating Artificial Neural Networks into Agent-Based Electricity Market Simulation

Christoph Fraunholz*, Emil Kraft, Dogan Keles, Wolf Fichtner

Karlsruhe Institute of Technology, Chair of Energy Economics, Hertzstraße 16, D-76187 Karlsruhe

July 10, 2020

Abstract

Machine learning and agent-based modeling are two popular tools in energy research. In this article, we propose an innovative methodology that combines these methods. For this purpose, we develop an electricity price forecasting technique using artificial neural networks and integrate the novel approach into the established agent-based electricity market simulation model PowerACE. In a case study covering ten interconnected European countries and a time horizon from 2020 until 2050 at hourly resolution, we benchmark the new forecasting approach against a simpler linear regression model as well as a naive forecast. Contrary to most of the related literature, we also evaluate the statistical significance of the superiority of one approach over another by conducting Diebold-Mariano hypothesis tests. Our major results can be summarized as follows. Firstly, in contrast to real-world electricity price forecasts, we find the naive approach to perform very poorly when deployed model-endogenously. Secondly, although the linear regression performs reasonably well, it is outperformed by the neural network approach. Thirdly, the use of an additional classifier for outlier handling substantially improves the forecasting accuracy, particularly for the linear regression approach. Finally, the choice of the model-endogenous forecasting method has a clear impact on simulated electricity prices. This latter finding is particularly crucial since these prices are a major results of electricity market models.

Keywords: Agent-based simulation; Artificial neural network; Electricity price forecasting; Electricity market

*Corresponding author, email address: *christoph.fraunholz@kit.edu*

1 Introduction

Since the liberalisation of electricity markets, wholesale spot markets have steadily gained importance in determining the economics of generation, storage and demand units in the energy system. Even though a major share of final electricity generation – and likewise consumption – is still traded on the forward market or via bilateral contracts, the spot market price is the eventual realization that determines the opportunity and the future expectations on electricity prices. Typically, on a day-ahead basis, demand and supply bids are matched in auctions on electricity exchanges in many parts of the world to determine electricity prices. In understanding the complex techno-economic interdependencies in the price formation on electricity markets, many efforts have been made to model market logic and actors' behavior in both the long-term investment and the short-term operational perspective.

Besides approaches deploying mathematical optimization (e.g., Leuthold et al., 2008), system dynamics (e.g., Petitet, 2016) and equilibrium models (e.g., Just and Weber, 2008), simulation models depicting the individuals' behavior constitute one major research stream. After evolving in the early 2000s, so-called agent-based simulation models (ABM) are today widely applied to address research questions dealing with electricity price developments, energy policy measures, generation adequacy, generation expansion planning, market design and market performance. In ABMs, system effects emerge from depicting and simulating the individual agents' behavior. The most popular ABMs developed for the analysis of European electricity markets include AMIRIS (Reeg et al., 2012), EMLab (Chappin et al., 2017), and PowerACE (Genoese, 2010). For a broad overview on further applications of ABMs in the energy context, please refer to the several review papers available in the literature (Guerci et al., 2010; Hansen et al., 2019; Ringler et al., 2016; Weidlich and Veit, 2008; Zhou et al., 2007).

In ABMs, each agent derives its decisions model-endogenously. Thus, a key challenge in accurately modeling agents' behavior lies in providing adequate expectations for the future developments within the model. Hereby, agents typically base their decisions on fundamental factors, such as techno-economic investment parameters or variable costs of electricity generation, and on market price expectations. The need for the latter motivates the essential role of price forecasting in ABMs, as the price forecasts have crucial interdependencies with agents behavior and thus the plausibility of the simulation results.

However, hardly any methodology or evaluation of the quality of model-endogenous price forecasting has been presented in the literature in the past (see Section 2). As this issue is crucial to model accuracy and has been treated only rudimentary, this contribution addresses the scope of developing adequate model-endogenous short-term price forecasts and to evaluate them using PowerACE, an established ABM developed at Karlsruhe Institute of Technology (KIT). PowerACE offers the opportunity to conduct case studies depicting the interconnected European electricity market with a time horizon until 2050. We investigate and report both, the forecasting accuracy and the emerging simulation results under different price forecasting approaches. In brief, the main highlights and contributions of this paper are:

- We describe the implementation and interdependencies of model-endogenous price forecasts in long-term ABMs for interconnected electricity markets.
- We assess the suitability and the performance of naive, linear regression and artificial neural network (ANN) based forecasting approaches.
- We evaluate the impact of improved price forecasts for the agents on the simulation results emerging on a European energy system level.

The remainder of the paper is structured as follows. Section 2 provides a literature review on machine learning (ML) applications in the energy context in general and the integration of such methods in ABMs in particular. Section 3 introduces the PowerACE model, outlines the challenges of model-endogenous price forecasting and explains the developed approaches as well as their implementation. In Section 4, a case study of the interconnected European electricity market until 2050 is presented and the accuracy of the developed forecasting approaches is evaluated. Section 5 comprises the main findings, draws conclusions and provides an outlook on future research fields in the further development of ABM.

2 Literature Review and Research Gap

Since literature matching the exact scope of this paper is scarce, the review provided in the following starts with a rather generic overview of ML approaches applied for (price) forecasting in the energy domain. Then, we present in more detail the few directly relevant publications and outline the research gap this paper aims to fill.

Forecasting is one of the most popular fields in energy economics. Herein, as in many other research fields, ML approaches gain more and more importance. Among the family of ML approaches, ANN can be considered the most popular and most widespread. As shown in a pioneering study by Adya and Collopy (1998), well-designed ANN approaches are capable to outperform traditional forecasting approaches from econometrics and were computationally manageable at the end of the last millennium. With increasing computational capacities in the past years, ML has conquered the forecasting domain with various algorithms fitted to even more various scopes.

In the energy context, major applications include load forecasting (pioneering studies by Lee et al., 1992; Liu et al., 1991; Park et al., 1991), renewable feed-in (see, e.g., Yadav and Chandel, 2014, for an extensive review on solar), redispatch forecasting (Staudt et al., 2018) or even more complex tasks such as photovoltaic potential assessment (Mainzer et al., 2017).

However, the most prominent field for ANN applications remains price forecasting and particularly the forecasting of electricity spot market prices (for conciseness, in the remainder referred to as *electricity prices*). Forecasting electricity prices with ANN has been pervasively studied (see, e.g., Catalão et al., 2007; Conejo et al., 2005; Pindoriya et al., 2008; Rodriguez and Anders, 2004, for early studies). The thorough review on electricity price forecasting by Weron (2014) provides the reader a well-elaborated chapter on different structures and applications of ANN. Since the publication of this review paper, literature on ANN applications in electricity price forecasting has further augmented. Ghoddusi et al. (2019) provide a review on ML in energy economics, with an updated review on ANN studies forecasting electricity prices. Among the most influencing studies are Bento et al. (2018), Dudek (2016), Keles et al. (2016a), Lago et al. (2018a,b), Peng et al. (2018), Singh et al. (2017) and Wang et al. (2017), which all apply ANN in methodological variations to forecast electricity prices in different market areas. In addition to the review by Ghoddusi et al. (2019), recent studies by Giovanelli et al. (2018), Oksuz and Ugurlu (2019) and Ugurlu et al. (2018) provide further investigations and case studies on how to accurately forecast electricity prices in national spot markets with the use of ANNs.

Apart from the electricity spot market, ANNs are as well deployed to other electricity-related prices, such as balancing reserve market prices (Kraft et al., 2019, 2020) and energy prices for commodities like carbon emission certificates (Fan et al., 2015; Sun et al., 2016) or crude oil (Ding, 2018; Huang and Wang, 2018; Jammazi and Aloui, 2012; Moshiri and Foroutan, 2006; Yu et al., 2017; Zhao et al., 2017).

Let us now move on to the more specific field of implementing forecasting and ML techniques into ABMs of electricity markets. In a recent review paper, Prasanna et al. (2019) differentiate between two use case categories in this context. Firstly, ML methods can be used to forecast external input data, which is subsequently being used in an ABM. Secondly, ML algorithms may be applied to implement the learning behavior of the agents.

An example of the first use case category is provided in Scheidt (2002), where an ANN is trained to forecast electricity prices. The forecasts created by the ANN are then used to derive trading strategies that are deployed in a subsequently applied ABM. However, unlike in our approach, the ANN is not retrained using simulation results but only used in a static way.

Most publications falling into the second use case category identified by Prasanna et al. (2019) apply relatively simple reinforcement learning approaches like Q-learning (e.g., Esmaeili Aliabadi et al., 2017) or Erev-Roth learning (e.g., Mengelkamp et al., 2018; Zhou et al., 2011). Still, some noteworthy exceptions using supervised learning exist, which are addressed next.

Wehinger et al. (2013) present an ABM covering four European countries (France, Germany, Italy, Switzerland) with model-endogenous adaptive price forecasting based on multiple linear regression. The agents use these price forecasts to determine optimal trading decisions. As the simulation moves on, the price forecasting model is continuously updated using the latest available simulation outcomes. Despite the proximity to our concept, there are four major distinctions. Firstly, the regression model mostly relies on autoregressive terms and only includes few exogenous variables (temperature, wind forecast and oil price). Secondly, a linear regression rather than an ANN is used. Thirdly, unlike in our approach, effects in the neighbouring countries are not explicitly considered in the price forecasts. Finally, only a relatively short time horizon of few years is covered, whereas the time horizon in our work covers 2020 through 2050.

Pinto et al. (2012, 2016) use an ABM of the Iberian electricity market and implement different adaptive price forecasting techniques, such as feedforward ANNs or support vector machines. Although their scope of work is closely related to ours, the paper at hand can be seen as an extension in terms of several aspects. Firstly, Pinto et al. only consider very short time periods of two months rather than a multi-decade setting as we do. Secondly, a very basic ANN configuration is applied and only the Iberian market is modelled whereas we consider a much more complex setup with ten interconnected market areas. Finally and most importantly, Pinto et al. do not provide statistical evidence of any forecast's superiority over the other benchmarks considered.

We can conclude that given the scarce literature on applying ML for model-endogenous price forecasting in ABMs of electricity markets, an important research gap with regard to improving such simulation models opens up. Against this background, the following Section 3 introduces an innovative and unique methodology, that combines the two popular research streams of ML and ABM. Before we move on, let us outline that model-endogenous forecasting brings along a number of additional challenges in comparison to forecasting in the general sense. Firstly, the feedback on simulated electricity prices needs to be considered. Poor forecasting accuracy leads to poor agent bidding behavior, which then leads to implausible simulated prices in the consecutive simulation step. These erroneous prices influence the forecasting in the next simulation step, and so on. Secondly, both, the diversity and the change in the composition of the national energy systems and in interconnection capacities between market areas over time requires an approach, that is flexible and capable to adapt to new price formation mechanisms (Lago et al., 2018b). Thirdly, the computational limitation needs to be considered in the implementation into a ABM framework such as PowerACE. As the model training and forecasting is carried out numerous times within a simulation run until 2050, each single forecasting procedure must remain computationally lean. Therefore, a trade-off between ANN architecture and training on one side and the computational performance on the other side needs to be carried out.

3 Methodology

This section starts with an overview of PowerACE, the existing ABM framework applied in this paper. Next, we describe in detail the developed ANN forecasting approach and its integration into PowerACE. Finally, some additional forecasting approaches are introduced, which are used as benchmarks to evaluate the performance of the developed ANN-based methodology.

3.1 Simulation Framework

3.1.1 Overview

PowerACE is an established agent-based simulation model, which was originally developed for the analysis of the German electricity market in long-term scenario analyses (see Keles et al., 2016b; Ringler et al., 2017; Fraunholz et al., 2019a, for some exemplary applications). The model covers different electricity market segments with a focus on the day-ahead market and different types of capacity remuneration mechanisms and runs at an hourly resolution (8760 h/a) over a typical time horizon from 2015 up to 2050.

Within PowerACE, several agents represent the associated market participants such as utility companies, regulators and electricity consumers (see Fig. 1). Most notably, the modelled electricity suppliers can decide on the daily dispatch of their conventional power plants and storage units as well as once per simulation year on the investment in new such facilities. Thus, the short-term and long-term decision levels are considered jointly and their interactions can be investigated. Ultimately, the development of the markets emerges from the simulated behavior of all agents.

In light of the European Commission's goal of creating a Single European Market for electricity, the importance of adequately considering cross-border effects in electricity market models increases. Thus, recent advancements of PowerACE focus on expanding the geographical scope to cover multiple countries, which obviously significantly increases the model complexity. In this context, Fraunholz et al. (2019b) concentrated on the long-term investment perspective of the model and developed a novel algorithm to solve the generation expansion planning problem in interconnected electricity markets. Ringler et al. (2017) focused on the short-term perspective and embedded a linear optimization approach into PowerACE. This optimization is a simplified representation of EUPHEMIA (NEMO Committee, 2019), the algorithm used for the real-world day-ahead market clearing process across multiple interconnected market areas.

Yet, to-date, cross-border effects are only rudimentally considered in an essential part of the day-ahead market simulation, namely the model-endogenous short-term electricity price forecasting of the agents in PowerACE. To provide some more context, we next introduce the different steps of the day-ahead market simulation with PowerACE. As the long-term investment perspective of the model is not in the focus of this paper, it is not further addressed.

3.1.2 Day-Ahead Market Simulation

Multiple traders per market area participate in the day-ahead market simulation with PowerACE. Most importantly, *supply traders* representing the major utility companies in a given market area prepare individual bids for each of their conventional power plants. Additionally, price-inelastic bids for demand, renewable feed-in and (optionally) pumped storage units are prepared by agents representing a single trader per market area, respectively. We concentrate on the procedure from the supply traders' point of view, for which the different steps in the day-ahead market simulation are illustrated in Fig. 2 and briefly described as follows.

(1) *Price forecasting.* According to theory, electricity generators in a competitive market environment are willing to offer electricity at the marginal generation cost. However, starting up a power plant leads to additional costs related to a higher fuel consumption and a reduced lifetime caused by material wear and tear. In order to account for this and prepare bids accordingly, it is important

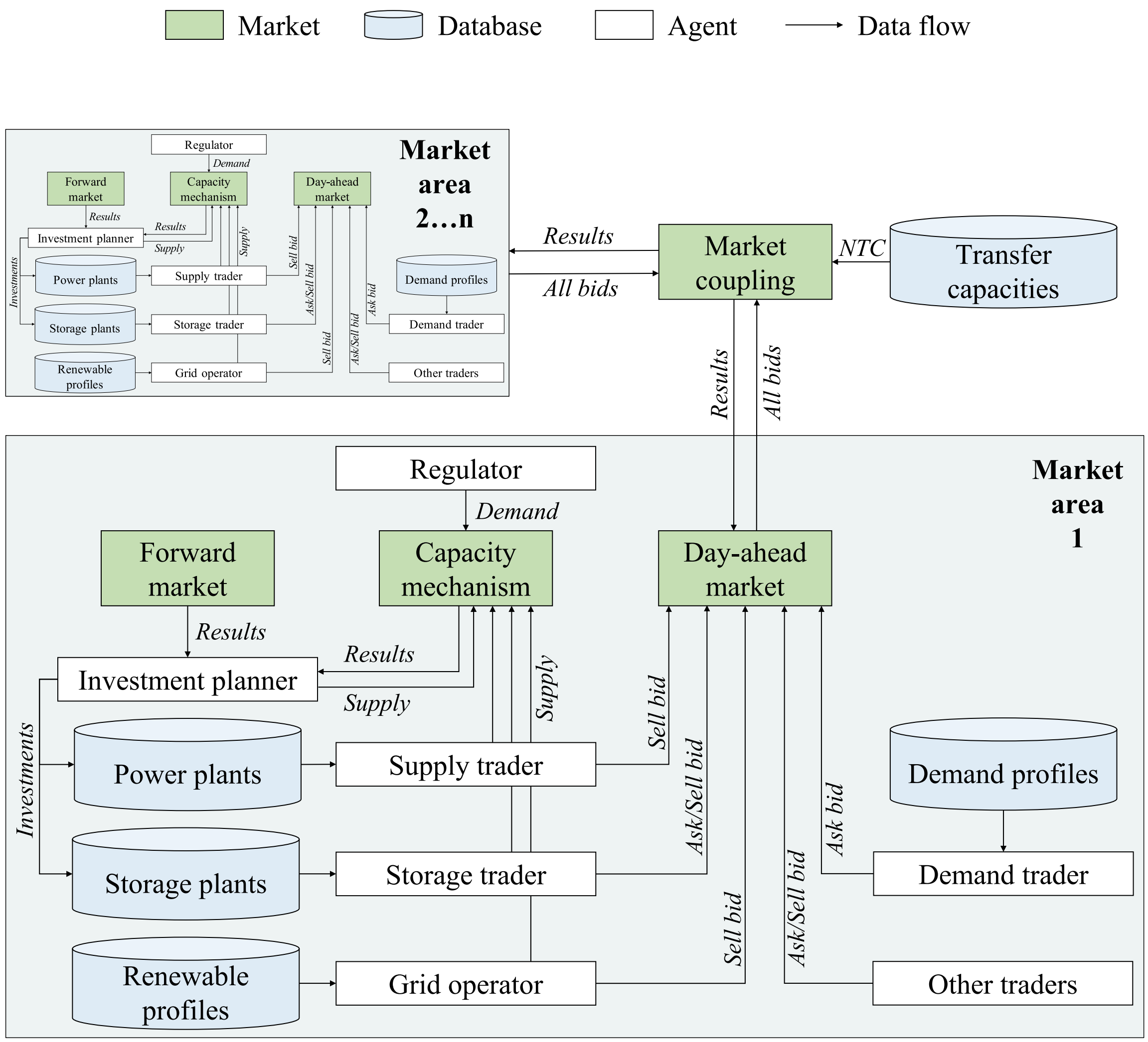


Figure 1: Schematic overview of the agent-based electricity market model PowerACE. The focus lies on the short-term simulation of the day-ahead markets and long-term investment decisions in a multi-country setup.

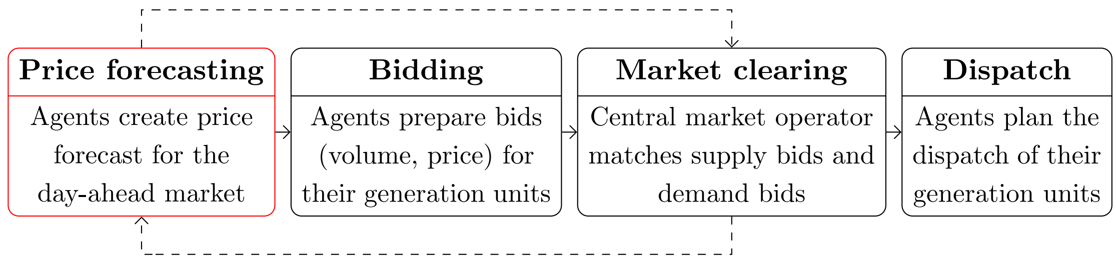


Figure 2: Steps of the day-ahead market simulation with PowerACE. Accurate price forecasts are essential, as they have a direct impact on the bidding of the agents, and thus an indirect impact on the outcomes of the market clearing process. The market outcomes of previous auctions in turn affect the price forecasting of the agents.

for the generators to estimate the running hours of a specific power plant on the next (simulation) day. Thus, the supply traders prepare a price forecast for all hours of the following day.

(2) *Bidding.* Based on the price forecast and their respective bidding strategies, the different supply trader agents now prepare bids for each of their power plants p and hour h of the following day. These bids consist of volume (MWh) and price (EUR/MWh). The bid volumes are determined by the installed capacity and under consideration of an exogenously given availability factor as well as a potential balancing reserve provision. In contrast, the bid prices depend both, on the type of the power plant and whether it is expected to run in the respective hour (i.e., $h \in \boldsymbol{H}_p^{\text{on}} \subseteq \boldsymbol{H}$) or expected not to run (i.e., $h \in \boldsymbol{H}_p^{\text{off}} \subseteq \boldsymbol{H}$). Table 1 provides an overview of the bidding strategies for the different situations. Please note that in all cases, the variable costs c_p^{var} of a power plant p play a crucial role. These are determined by the fuel price p_p^{fuel}, the power plant's net electrical efficiency η_p, the price of CO_2 emission allowances p^{CO_2}, the CO_2 emission factor of the fuel e^{fuel} and the costs for operation and maintenance $c_p^{\text{O\&M}}$ as shown in Eq. (1).

(3) *Market clearing.* All bids prepared by the supply trader agents are then submitted to a central market operator, which uses a clearing algorithm – formulated as a linear optimization problem – to determine electricity prices and cross-border electricity flows (Ringler et al., 2017). In the objective function, the economic welfare in the coupled electricity system is maximized (Eq. (2a)). Constraints include the energy balance in all market areas (Eq. (2b)) as well

as a limitation of the acceptance rates of demand bids (Eq. (2c)), supply bids (Eq. (2d)) and exchange flows between the different market areas (Eq. (2d)). The optimization problem is solved for each simulation hour, yet, we omit the index h for better readability. After the market has been cleared, the market outcome – in particular the information on which bids have been accepted – is returned to the different supply trader agents.

(4) *Dispatch.* Finally, all supply trader agents calculate the sum of their accepted hourly bid volumes, which results in their individual hourly load curve to serve. The agents then determine a cost-minimal dispatch of their power plant fleet, which serves this load curve under consideration of variable generation costs and start-up costs[1].

$$c_p^{\text{var}} = \frac{p_p^{\text{fuel}} + p^{\text{CO}_2} \cdot e^{\text{fuel}}}{\eta_p} + c_p^{\text{O\&M}} \tag{1}$$

$$\max_{x_d, x_s, x_{m_1,m_2}} \quad \sum_{m \in \boldsymbol{M}} \left(\sum_{d \in \boldsymbol{D_m}} (p_d \cdot q_d \cdot x_d) - \sum_{s \in \boldsymbol{S_m}} (p_s \cdot q_s \cdot x_s) \right) \tag{2a}$$

subject to

$$\underbrace{\sum_{d \in \boldsymbol{D_m}} (q_d \cdot x_d)}_{\text{Demand}} - \underbrace{\sum_{s \in \boldsymbol{S_m}} (q_s \cdot x_s)}_{\text{Supply}} + \underbrace{\sum_{m' \in \boldsymbol{M'_m}} \left(q_{m,m'}^{\max} \cdot x_{m,m'} - q_{m',m}^{\max} \cdot x_{m',m} \right)}_{\text{Exchange flows}} = 0 \quad \forall m \in \boldsymbol{M} \tag{2b}$$

$$0 \le x_d \le 1 \qquad \forall d \in \boldsymbol{D_m}, \forall m \in \boldsymbol{M} \tag{2c}$$

$$0 \le x_s \le 1 \qquad \forall s \in \boldsymbol{S_m}, \forall m \in \boldsymbol{M} \tag{2d}$$

$$0 \le x_{m_1,m_2} \le 1 \quad \forall m_1, m_2 \in \boldsymbol{M} \tag{2e}$$

[1] Formally, this step requires to solve a mixed-integer linear optimization problem. However, to save computational resources, a heuristic approach is applied, such that only close-to-optimal solutions can be guaranteed.

where

(Decision variables)

x	bid acceptance rate [–]

(Parameters)

p	bid price [EUR/MWh]
q	bid volume [MWh]

(Indices)

d	demand bid
s	supply bid
m	market area

(Sets)

$\boldsymbol{M}$	simulated market areas
$\boldsymbol{M'_m}$	market areas connected to market area m
$\boldsymbol{D_m}$	demand bids submitted in market area m
$\boldsymbol{S_m}$	supply bids submitted in market area m

It is important to realize that the model-endogenous price forecasts have a direct impact on the bidding of the different supply trader agents, which in turn drives the outcome of the market clearing process (cf. Fig. 2). At the same time, the price forecasting approaches applied in this paper are continuously updated during the simulation. For this purpose, the market outcomes of previous auctions are used as input data. In other words, there exists a mutual dependency between price forecasts and market outcomes. Thus, poor price forecasts lead to distorted, unsound bidding behavior and ultimately distorted market outcomes. This aspect is crucial, since simulated day-ahead market electricity prices are typically one of the major results of electricity market models.

As previously mentioned, PowerACE was originally developed to analyze the German electricity market. If only a single market area is considered, model-endogenous price forecasts are relatively simple to implement due to the limited number of price drivers. However, extending the model to a multi-country setup heavily increases the complexity of creating reasonably accurate price forecasts for all considered market

Table 1: Overview of power plants' hourly bidding prices $b_{p,h}$ depending on the type of the power plant and the expected online hours. Source: Fraunholz et al. (2020).

Case (1):	Power plant p (base-/medium-/peak-load) is in the market in all hours h[1]	
	$b_{p,h} = c_p^{\text{var}}$	$\forall h \in \boldsymbol{H}_p^{\text{on}} = \boldsymbol{H}$
Case (2):	Power plant p (base-load) is in the market in some hours h[2]	
	$b_{p,h} = c_p^{\text{var}}$	$\forall h \in \boldsymbol{H}_p^{\text{on}} \subseteq \boldsymbol{H}$
	$b_{p,h}^{\text{min}} = c_p^{\text{var}} - c_p^{\text{start}}/t_p^{\text{off}}$	$\forall h \in \boldsymbol{H}_p^{\text{off}} \subseteq \boldsymbol{H}$
	$b_{p,h}^{\text{rest}} = c_p^{\text{var}}$	$\forall h \in \boldsymbol{H}_p^{\text{off}} \subseteq \boldsymbol{H}$
Case (3):	Power plant p (medium-/peak-load) is in the market in some hours h[3]	
	$b_{p,h} = c_p^{\text{var}} + c_p^{\text{start}}/t_p^{\text{on}}$	$\forall h \in \boldsymbol{H}_p^{\text{on}} \subseteq \boldsymbol{H}$
	$b_{p,h} = c_p^{\text{var}} + c_p^{\text{start}}/\Delta t$	$\forall h \in \boldsymbol{H}_p^{\text{off}} \subseteq \boldsymbol{H}$

[1] If a power plant is expected to always be in the market, no start-up costs occur and the hourly bids $b_{p,h}$ therefore only consist of the variable costs c_p^{var}.

[2] Base-load power plants are expected to temporarily accept market prices below their marginal generation costs in order to avoid start-up costs in subsequent hours. Thus, variable costs are bid for the expected running hours $\boldsymbol{H}_p^{\text{on}}$ and two different bids are created for each hour $h \in \boldsymbol{H}_p^{\text{off}}$ – the minimum running load of the power plant is bid at variable costs minus avoided start-up costs c_p^{start}, while the remaining load is bid at variable costs. The avoided start-up costs are evenly distributed among the expected offline time t_p^{off}.

[3] If a medium- or peak-load power plant is expected to be in the market only in few hours or never, the hourly bids consist of variable costs and start-up costs. For expected online times t_p^{on} longer than one hour, start-up costs are distributed evenly.

areas. Thus, this paper aims to develop, implement and test novel approaches in this regard. To the best knowledge of the authors, this crucial aspect with regard to model accuracy is mostly overlooked to date by simulation-based electricity market models in the scientific literature (cf. Section 2).

Before delving into the methodological details of the proposed new price forecasting approaches, we have to mention that a single price forecast is created in each simulated market area, which is then used by all supply traders allocated to a given market area. We choose this approach first and foremost to reduce the computational burden. Moreover, the scope of this paper is to highlight the general suitability of ANNs in the context of electricity market simulation models. However, extending our approach to a separate price forecast for each supply trader is straightforward, since multiple instances of an ANN can easily be created by using different random number seeds. Moreover, network architecture and training strategies could be varied to further diversify the price forecasts.

3.2 Artificial Neural Network Model

3.2.1 Preparation of Input Data

The objective of the implemented ANNs is to find model-endogenous relationships between different input variables and the target variable, i.e., the simulated market prices. Since the day-ahead electricity markets are cleared such that a balance between supply and demand is ensured, drivers of both the supply and the demand side are relevant. Moreover, the market results in a given market area are crucially affected by the situation in directly or even indirectly interconnected market areas.

We aim to keep our ANNs as simple as possible and therefore base them solely on fundamental factors, used in similar form, e.g., by Keles et al. (2016a): expected electricity demand, expected feed-in of renewables, fuel prices, carbon prices, and available generation capacities. Please note that we always consider the variables of all modelled market areas, regardless of the market area for which the price forecast is carried out. This is because the electricity markets of the European countries are interconnected and therefore mutually influence each other. This is particularly relevant in the price formation process and therefore also in price forecasting as recently confirmed by Lago et al. (2018b). Given the model-endogenous character of our price forecasts and the fact that simulations up to 2050 are carried out, a few additional particularities need to be considered:

- As is common practice in electricity market models, renewables are assumed to bid their generation at 0 EUR/MWh. The feed-in of 1 MW renewable electricity is therefore essentially equivalent to a reduction in electricity demand of 1 MW. Thus, we combine electricity demand and renewable feed-in to a single variable per market area, the residual demand.

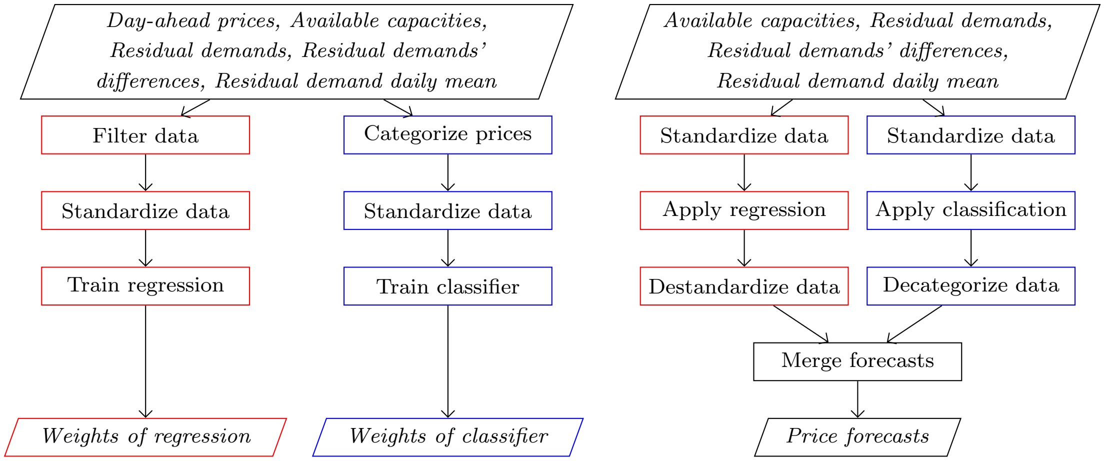
- Due to the non-availability of hourly resolved projections up to 2050 in the literature, we assume constant fuel and carbon prices over the course of a single year. In consequence, the simulated electricity prices do not contain intra-annual fluctuations caused by level variations of the fuel and carbon prices. We can therefore omit fuel and carbon prices from the list of input variables used in our price forecasting ANNs.

- PowerACE allows for investment decisions and decommissioning of old generation capacity at the end of each simulation year. Throughout a year, however, constant availability factors are used for all technologies except for nuclear power plants[2]. Thus, only the available generation capacities of market areas with substantial shares of nuclear power are included in the set of explanatory variables.

- The day-ahead price cap in European electricity markets is currently set at 3000 EUR/MWh. In practice, this limit is (almost) never reached. Contrary, due to the simulation horizon of PowerACE up to 2050, scarcity situations with extreme price spikes may well occur in our model. The same is true for hours with a surplus of renewable electricity generation and prices reaching 0 EUR/MWh or even becoming negative. These situations are still relatively rare in reality, yet are likely to occur substantially more often in future simulation years. Thus, unlike present real-world day-ahead price forecasts, our ANN approach needs to be able to consider such situations adequately.

Apart from time series for the residual demand in all modelled market areas and the available capacities in market areas with substantial shares of nuclear power, we also consider the first differences of the residual demand time series to account for auto-correlation in load and thus electricity prices (cf. Weron, 2014). Moreover, since the operation of pumped storage plants does not only depend on the level of the residual load in a given hour, but also on the load level throughout the day, the input data for our ANNs also includes the daily arithmetic mean of the residual load in the respective market area under consideration.

[2]Nuclear power plants are base-load power plants and therefore rely on as many running hours as possible. These units therefore typically carry out their annually required revisions in times of low electricity demand. Thus, seasonal patterns can be observed regarding the available capacities of nuclear power plants



(a) Training **(b)** Forecasting

Figure 3: Overview of the training (a) and forecasting (b) process of the artificial neural networks. Two different models are applied, one for price regression (red) and one for classification to consider extreme situations (blue), i.e., surplus generation setting the price at 0 EUR/MWh and scarcity resulting in a price of 3000 EUR/MWh.

3.2.2 Model Configuration and Training

For the price forecast using ANNs we apply a two-stage modeling approach, which is schematically illustrated in Fig. 3.

Firstly, a feedforward neural network is used for a regression[3] aiming to explain the simulated prices in dependence of the residual demands, their first differences and daily mean as well as the available capacities in all market areas. For the training of this model (Fig. 3a, red boxes), the input data is filtered to exclude outlier prices resulting from the must-run capacity exceeding the residual demand[4] (i.e., a price of

[3]Please note that we use the term *regression* to describe the general process of finding relationships between a set of input variables and a set of output variables, regardless of the specific method applied. Whenever we refer to *regression* in the meaning of a particular statistical method, we use the exact name of this method, e.g., *linear regression*, *logistic regression* or *non-linear regression*.

[4]In reality, even negative prices often occur in such situations. This is because some heat-controlled conventional power plants need to stay online to fulfill their heat delivery agreements. Moreover, renewable feed-in is often subsidized such that it can still operate profitably, even under (slightly) negative prices. In PowerACE, must-run conditions of conventional power plants are not modelled and all renewables offer their production at 0 EUR/MWh. Thus, prices of 0 EUR/MWh

0 EUR/MWh) or a scarcity situation (i.e., a price of 3000 EUR/MWh). Next, the explanatory variables and the response variable are standardized as shown in Eq. (3), where z denotes the standardized variable, x the non-standardized variable, $\overline{x}$ the mean of the sample and S the standard deviation of the sample. Standardization is a common procedure in machine learning to improve training speed and performance. The network is then trained with the standardized data.

$$z = \frac{x - \overline{x}}{S} \tag{3}$$

Secondly, another feedforward neural network is used to classify the simulated prices into 1) situations with a renewable surplus setting the price at 0 EUR/MWh, 2) regular situations with the price being set by any conventional power plant or storage unit, and 3) scarcity situations with peak prices of 3000 EUR/MWh as shown in Eq. (4). Please note, that the residual demands' differences do not have an impact on whether a renewable surplus or a scarcity situation occurs and are therefore omitted. For the training of the model (Fig. 3a, blue boxes), the simulated prices are first categorized and transformed using one-hot encoding. Then, as for the first ANN, the explanatory variables are standardized and the ANN is trained to obtain the weights of the classification network.

$$c = \begin{cases} 1, & \text{if } p = 0\,\text{EUR/MWh} \\ 2, & \text{if } p > 0\,\text{EUR/MWh} \wedge p < 3000\,\text{EUR/MWh} \\ 3, & \text{if } p = 3000\,\text{EUR/MWh} \end{cases} \tag{4}$$

The ANNs are trained with random initial weights once every simulation month to adequately consider recent simulation outcomes. After being trained, the ANNs are applied to provide day-ahead electricity price forecasts to the trading agents for every simulation day until the next training is carried out. The forecasting process is shown in Fig. 3b. The input data is first standardized using the respective time series characteristics (mean and standard deviation) of the training process. Using the same standardization in training and forecasting is essential to obtain reasonable forecasts, since the situations to be forecasted need to follow the same statistical process as the training data. Both the regression ANN and the classification ANN are then simultaneously applied to obtain forecasts of prices and price classifications.

After prediction, the forecasts are destandardized or set to the fixed value of the predicted class according to Eq. (5), respectively. If the classification predicts a regular situation ($\hat{c} = 2$), the price forecast of the regression ANN $\hat{p}_{\text{prelim}}$ determines

can only occur in our model, if the feed-in of renewables exceeds the residual demand.

$\hat{p}$. Yet, if according to the classification, a surplus of generation is predicted to set the price ($\hat{c} = 1$) or a scarcity situation is predicted to occur ($\hat{c} = 3$), the price forecast $\hat{p}$ is set to 0 EUR/MWh, or 3000 EUR/MWh, respectively. In the literature, this applied algorithm is also known as a regime-switching model (e.g., Keles et al., 2012; Swider and Weber, 2007).

$$\hat{p} = \begin{cases} 0\,\text{EUR/MWh}, & \text{if } \hat{c} = 1 \\ \hat{p}_{\text{prelim}}, & \text{if } \hat{c} = 2 \\ 3000\,\text{EUR/MWh}, & \text{if } \hat{c} = 3 \end{cases} \tag{5}$$

Table 2 provides an overview of the applied hyperparameters in the regression and classification ANNs. These parameters were found after intense testing and satisfy the trade-off between computational burden and forecasting accuracy. Most notably, we use a relatively large batch size of 512 to increase the chance of all three price classes being included in the majority of the batches. In order to avoid overfitting, we apply a L2-regularization. This means that the loss term to be minimized during training is supplemented by a regularization term r, which is calculated as the squared Euclidean norm of the weight vector $\boldsymbol{w}$, multiplied by a small coefficient ε as shown in Eq. (6). Moreover, early stopping helps to reduce the risk of overfitting and at the same time limits the time required for the model training. The training data consists of simulation results from the previous 8760 hours of the simulation and is adjusted for each new model training using a rolling horizon approach.

$$r = \varepsilon \cdot \|\boldsymbol{w}\|_2^2 = \varepsilon \cdot (w_1^2 + w_2^2 + ... + w_n^2) \tag{6}$$

We are well aware that other and more sophisticated types of ANN than simple feedforward networks exist. Yet, as also stated by Prasanna et al. (2019), in the context of ABMs with multiple agents interacting dynamically, computationally efficient lean algorithms are preferable for model-endogenous tasks. We apply two ANNs (classification and regression, as described above) in each of the ten market areas, which are trained monthly over a simulation period of 31 years (2020 until 2050). Consequently, we end up with $2 \cdot 10 \cdot 12 \cdot 31 = 7440$ model trainings to be carried out. Thus, despite acknowledging the potential improvements that recurrent neural networks or other advanced types of ANN may bring along, we refrain from implementing such approaches.

Table 2: Overview of the applied hyperparameters in the regression and classification ANNs.

Hyperparameter	Regression ANN	Classification ANN
Model class	Feedforward network	Feedforward network
Input variables[1]	22	12
Output variables[2]	1 (day-ahead price)	3 (price categories)
Hidden layers	2	1
Neurons in hidden layers	20/15	10
Activation functions	Rectified linear unit/Rectified linear unit/Identity	Rectified linear unit/Softmax
Weight initialization	Xavier uniform (Glorot and Bengio, 2010)	Xavier uniform (Glorot and Bengio, 2010)
Updater	Adam (Kingma and Ba, 2017) with $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$	Adam (Kingma and Ba, 2017) with $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$
Loss function	Mean squared error	Multiclass cross-entropy
Regularization	L2 with coefficient 10^{-4}	L2 with coefficient 10^{-4}
Training data size	8760 (rolling horizon)	8760 (rolling horizon)
Batch size	512	512
Number of epochs	200	200
Early stopping	10 epochs w/o improved loss	10 epochs w/o improved loss

[1] As shown later in Section 4.1, ten market areas are modelled. The regression ANN uses residual demands, their first differences and the available capacities in all market areas. Moreover, the daily arithmetic mean of the residual load in the respective market area under consideration is included. Please note, however, that only the available capacities in France are considered, since it is the only modelled country with a substantial share of nuclear power installed and constant availabilities are assumed for all other technologies. Contrary, the classification ANN omits the first differences of the residual demands, as they do not have an impact on whether a renewable surplus or a scarcity situations occurs.

[2] Since separate forecasting models are created for each market area, the only output variable of the regression ANN is the day-ahead electricity price in the respective market area. Contrary, the classification ANN predicts the probabilities of an hour belonging to one of three classes, thus it has three output variables.

3.2.3 Technical Implementation

The agent-based simulation model PowerACE is programmed in Java. For this reason, we use *Deeplearning4J*[5], an established deep learning programming library written for Java to embed the novel price forecasting approaches based on ANNs into the existing modeling framework.

PowerACE considers multiple market areas, for each of which a separate price forecast needs to be carried out. Since these forecasts can be calculated fully independent of each other, we use multi-threading to speed-up the training process. We run PowerACE on a machine with an *AMD Ryzen Threadripper 2950X* CPU (16 cores at 4.0 GHz) and 128 GB main memory (RAM). As we want to ensure deterministic behavior, the ANNs are initialized with an identical random number seed in all simulations carried out.

3.3 Benchmark Models

In order to assess the accuracy of the implemented price forecasts based on ANNs, it is necessary to compare the outcomes with those of some benchmarks. For this purpose, we implement a naive approach as well as a linear regression approach, which are briefly described in the following paragraphs.

3.3.1 Naive Price Forecast

The basic idea of the naive price forecast is to use a potential correlation between prices in a given hour and those of the same hour on the previous day. Alternatively, it is also common to use the hour of the same weekday in the previous week, to account for differences between different types of days. More precisely, the price forecasts $\hat{p}_h$ in hour h are calculated very simply as $\hat{p}_h = p_{h-x}$, where x denotes the respective lag of 24 or 168 hours. Please note that despite the obvious simplicity of this approach, more advanced but insufficiently calibrated models often fail to outperform the naive benchmark (Conejo et al., 2005).

3.3.2 Linear Regression Model

A linear regression model is a reasonable additional benchmark, as it ranges between the naive forecast and the ANN approach with regard to model complexity. Anal-

[5] `https://deeplearning4j.org/`

ogously to the ANN approach, the implemented linear regression approach consists of the two separate steps previously introduced in Section 3.2.2.

However, the regression part is carried out as a multiple linear regression rather than as an ANN. The corresponding relationship is shown in Eq. (7), where $\boldsymbol{\beta}$ denotes the vector of regression coefficients, $\boldsymbol{x_h}$ the vector of explanatory variables in hour h, and p_h the independent variable, i.e., the price in hour h.

$$p_h = \boldsymbol{\beta} \cdot \boldsymbol{x_h} \tag{7}$$

Similarly, a multinominal logistic regression is applied for classification instead of the second ANN. With K denoting the number of price categories (in our case $K = 3$), $\boldsymbol{\beta_k}$ the vector of regression coefficients for price category k, and $\boldsymbol{x_h}$ the vector of explanatory variables in hour h, Eq. (8) presents the probability of a given hour h falling into price category k. For the forecast, the category with the highest estimated probability ultimately determines the expected category $\hat{c}_h$ of the hour h.

$$\Pr(c_h = k) = \begin{cases} \dfrac{e^{\boldsymbol{\beta_k} \cdot \boldsymbol{x_h}}}{1 + \sum_{k'=1}^{K-1} e^{\boldsymbol{\beta_{k'}} \cdot \boldsymbol{x_h}}}, & \text{for } k \neq K \\ \dfrac{1}{1 + \sum_{k'=1}^{K-1} e^{\boldsymbol{\beta_{k'}} \cdot \boldsymbol{x_h}}}, & \text{for } k = K \end{cases} \tag{8}$$

Please note that individual models are used in each considered market area, yet we omit the index m for better readability. Since a linear predictor function is used in both, the regression and the classification part, we can interpret this benchmark as a linear approach, contrary to the non-linear character of the ANNs.

Please note that the type of relationship between electricity prices and the various explanatory variables is likely to change throughout the simulation in an a priori unknown fashion. Consequently, we refrain from applying non-linear regression models as an additional benchmark.

3.3.3 Models Without Classifier

Finally, in order to assess the benefit of handling outliers separately by means of a classifier, both, the ANN approach and the linear regression approach are additionally tested in configurations without classifiers, i.e., only the red parts of Fig. 3 are applied for these cases.

4 Evaluation of the Forecasting Approaches

In this section, we conduct a multi-country long-term case study using PowerACE with the newly implemented price forecasting methods. To start with, we provide an overview of the data used and the scenarios under investigation. Then, we compare the forecasting performance of the ANN approach and the benchmarks. Finally, we show how the forecasting accuracy affects the eventual simulated market outcomes, i.e., the day-ahead electricity prices.

4.1 Data Sources and Scenario Setup

As introduced in Section 3.1, PowerACE is a detailed bottom-up simulation model and therefore requires substantial amounts of input data. Table 3 provides an overview of the data used in all simulations presented in the following as well as the respective sources. Since a major objective of the developed price forecasting methodologies is the adequate consideration of cross-border effects, the applied version of PowerACE covers ten interconnected European countries, all of which are modelled considering their respective real-world market design[6] (see Fig. 4).

We run a total of five simulations with identical input data and only vary the applied day-ahead price forecasting methodology. The simulations are carried out with an hourly resolution and cover the time horizon from 2020 to 2050. The different forecasting approaches investigated are as follows:

- Naive persistence forecast with lag of 24 hours (*Naive24*),
- Multiple linear regression with multinominal logistic regression classifier (*LRw/C*),
- Feedforward neural network with feedforward neural network classifier (*ANNw/C*),
- Multiple linear regression without classifier (*LRw/oC*),
- Feedforward neural network without classifier (*ANNw/oC*).

In the remainder of this paper, we focus on the first three approaches, while the additional model runs without classifier are only briefly addressed. However, the complete results of all simulations are included in Appendix A.

[6] For details on the different market design options see Bublitz et al. (2019).

Table 3: Overview of the input data used in all simulations carried out with PowerACE. The table has been adopted from a previous study (Fraunholz et al., 2019a) since we make use of the exact same data sets.

Input data type	Resolution	Sources and comments
Conventional power plants	unit level	S&P Global Platts (2015), and own assumptions
Fuel prices	yearly	EU Reference Scenario (de Vita et al., 2016)
Carbon prices	yearly	EU Reference Scenario (de Vita et al., 2016), scaled to reach 150 EUR/t_{CO_2} in 2050
Investment options	yearly	Louwen et al. (2018); Schröder et al. (2013); Siemens Gamesa (2019), and own assumptions
Interconnector capacities	yearly	Ten-Year Network Development Plan (ENTSO-E, 2016)
Electricity demand	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to the yearly demand given in the EU Reference Scenario (de Vita et al., 2016)
Renewable feed-in	hourly, market area	historical time series of 2015 (ENTSO-E, 2017), scaled to reach an overall renewable share in relation to electricity demand of 80 % in 2050

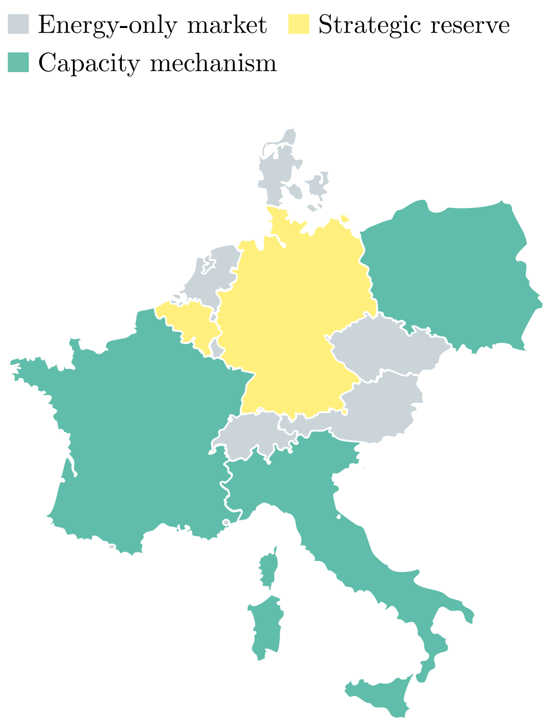


Figure 4: Overview of the real-world electricity market designs implemented in the different countries covered by PowerACE. Only the grey market areas rely on an energy-only market, whereas the other market areas use different long-term investment support schemes, either a strategic reserve (yellow) or a capacity mechanism (green). However, as theory suggests no impact of these mechanisms on the short-term bidding behavior is modelled.

4.2 Forecasting Performance

In order to compare the forecasting performance of the different approaches under investigation, we apply two common error metrics in the field of forecasting. Firstly, we consider the *mean absolute error* (MAE) between the forecasted hourly electricity prices $\hat{p}$ and their simulated realizations p. For a given year y and market area m, the MAE can be calculated according to Eq. (9). Secondly, in order to account for the general increase of the price level over the course of the simulation (cf. Section 4.3), we also calculate the *mean absolute percentage error* (MAPE) according to Eq. (10). Please note that we choose the yearly mean prices $\overline{p}_{m,y}$ as the denominator rather than using the hourly realizations $p_{m,y,h}$ in order to avoid the adverse effect of dividing by very low values close to zero in case of very low simulated prices.

$$e_{m,y}^{\text{MAE}} = \frac{1}{8760} \sum_{h=1}^{8760} |p_{m,y,h} - \hat{p}_{m,y,h}| \tag{9}$$

$$e_{m,y}^{\text{MAPE}} = \frac{1}{8760} \sum_{h=1}^{8760} \frac{|p_{m,y,h} - \hat{p}_{m,y,h}|}{\overline{p}_{m,y}} \quad \text{with} \quad \overline{p}_{m,y} = \frac{1}{8760} \sum_{h=1}^{8760} p_{m,y,h} \tag{10}$$

While metrics like the MAE or the MAPE are useful to get a first impression of one forecast's superiority over another, they do not provide any notion of the statistical significance of such a conclusion. Many electricity price forecasting papers in the literature neglect this aspect. In contrast, as recommended by Weron (2014), we run one-sided Diebold-Mariano tests (Diebold and Mariano, 1995) on the time series of *absolute errors*. Given the structure of the Diebold-Mariano test, we conduct one-on-one tests for each of the combinations of two forecasting approaches in our set. As we test the hypothesis that one approach is better than the other in both directions, this leads to 20 tests per country and a total of 200 tests. Due to the large amount of data available (31 years from 2020 until 2050 at hourly resolution, i.e., a total of $31 \cdot 8760 = 271560$ data points), these hypothesis tests should then be able to state at a high significance level, whether the mean of the compared time series of *absolute errors* is statistically different from zero (i.e., one forecast is superior to the other).

In Tables 4–6, we provide the MAEs and MAPEs in all countries and years for the naive persistence approach (*Naive24*), the linear regression approach with classifier (*LRw/C*) and the ANN approach with classifier (*ANNw/C*), respectively. For a quick visual overview, the same data are presented as heatmaps for selected simulation years in Figs. 5 and 6. The results of the additional simulations without classifier (*LRw/oC*, *ANNw/oC*) are provided in Tables 7 and 8 in Appendix A.

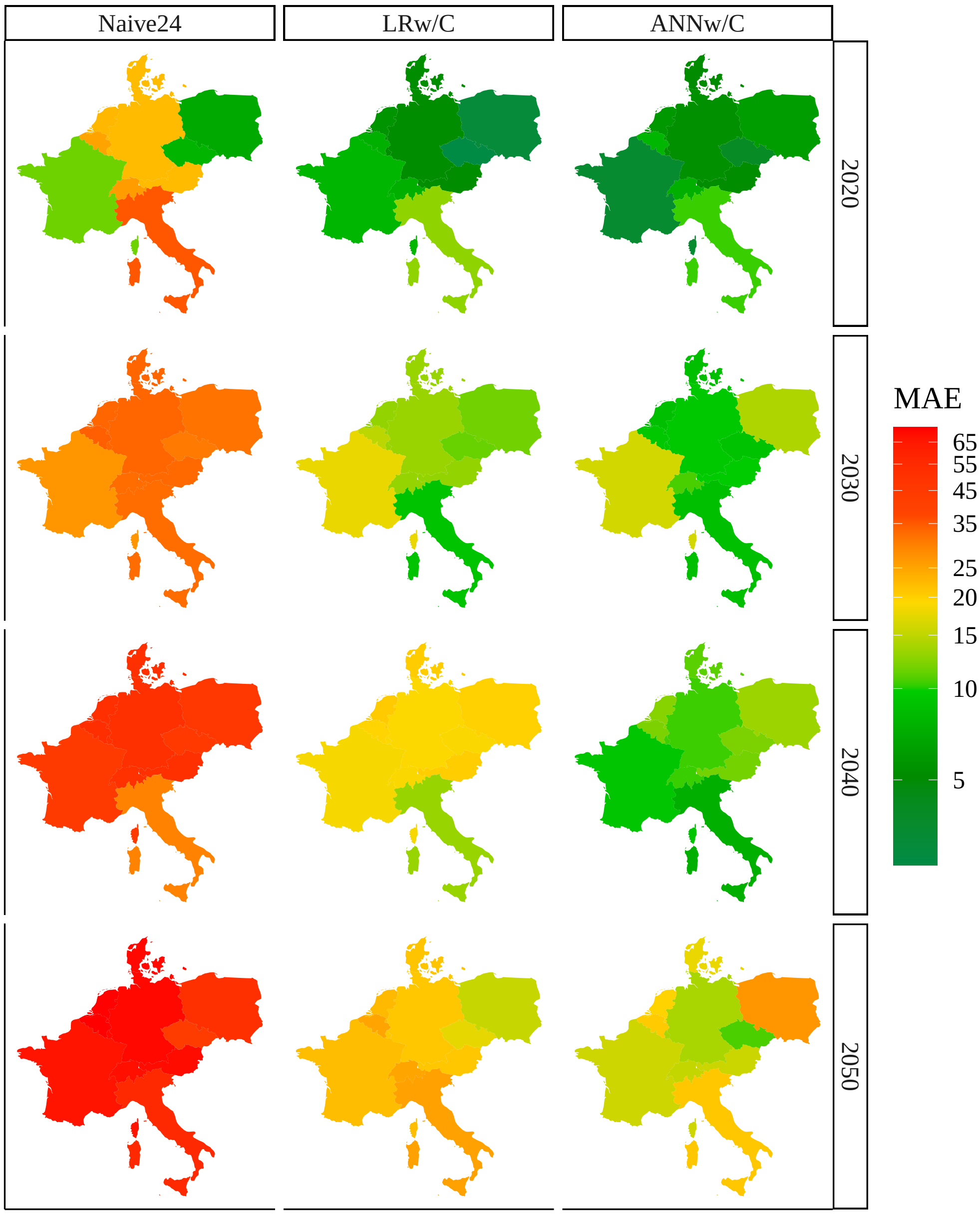


Figure 5: Mean absolute errors (MAEs) of the different price forecasting approaches in selected simulation years. The linear regression (*LRw/C*) and even more so the artificial neural network approach (*ANNw/C*) clearly outperform the persistence forecast (*Naive24*). Driven by the general increase of the price level (cf. Section 4.3), the MAEs increase over the course of the simulation for all forecasting approaches considered.

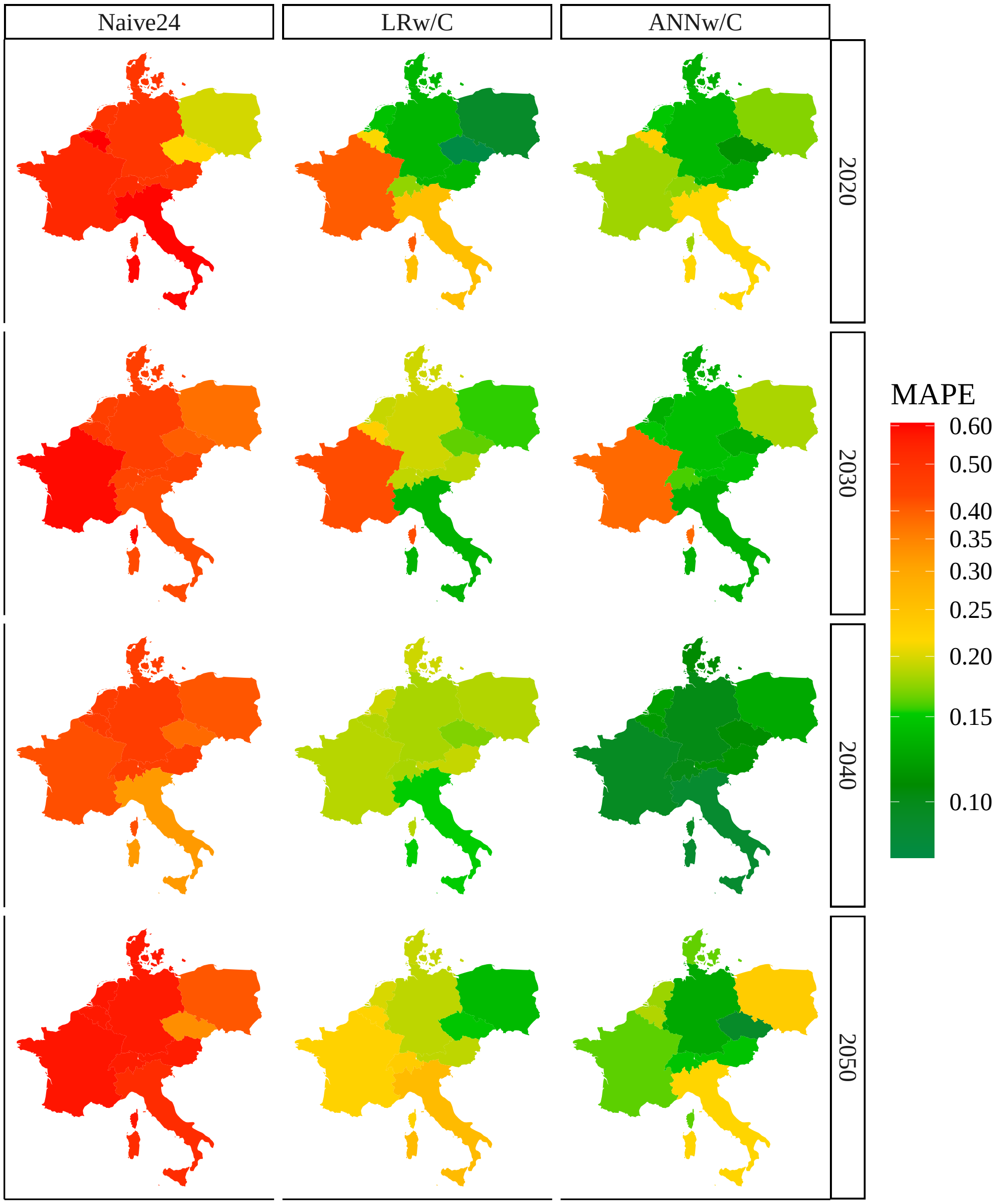


Figure 6: Mean absolute percentage errors (MAPEs) of the different price forecasting approaches in selected simulation years. The linear regression (*LRw/C*) and even more so the artificial neural network approach (*ANNw/C*) clearly outperform the persistence forecast (*Naive24*). In contrast to the MAE, the MAPE accounts for the general increase of the price level (cf. Section 4.3) and therefore remains more stable over the course of the simulation.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	22.2	25.2	7.8	22.2	11.5	22.2	35.2	22.7	6.9	26.0	0.49	0.61	0.22	0.49	0.53	0.49	0.60	0.50	0.20	0.52
2021	23.7	26.8	13.1	23.8	11.9	23.7	34.7	24.2	7.7	27.1	0.49	0.61	0.31	0.49	0.54	0.49	0.58	0.49	0.20	0.51
2022	24.5	28.0	20.0	24.5	12.3	24.4	34.7	24.8	11.5	27.5	0.48	0.62	0.41	0.48	0.54	0.48	0.56	0.48	0.27	0.50
2023	27.3	30.5	26.2	27.2	13.0	27.3	34.4	27.5	20.5	29.4	0.49	0.63	0.47	0.49	0.56	0.49	0.54	0.49	0.39	0.50
2024	45.8	44.4	45.4	45.8	18.7	45.9	33.4	44.5	39.8	46.7	0.64	0.75	0.63	0.64	0.69	0.64	0.50	0.63	0.58	0.64
2025	55.4	54.0	55.0	55.3	19.6	55.4	33.7	54.8	50.9	55.8	0.68	0.69	0.67	0.68	0.67	0.68	0.49	0.68	0.63	0.68
2026	42.4	43.2	41.8	42.2	22.1	42.4	33.1	42.4	39.1	42.3	0.57	0.60	0.56	0.57	0.73	0.57	0.47	0.57	0.51	0.56
2027	30.2	32.0	29.2	30.2	15.3	30.3	33.3	30.4	28.5	29.9	0.45	0.50	0.43	0.45	0.60	0.45	0.46	0.45	0.39	0.44
2028	30.6	32.3	29.2	30.7	17.5	30.7	32.6	30.7	29.4	30.1	0.44	0.49	0.41	0.44	0.62	0.44	0.45	0.45	0.39	0.43
2029	31.5	33.4	29.8	32.0	20.3	32.0	32.8	31.9	30.6	31.5	0.44	0.49	0.41	0.45	0.63	0.45	0.44	0.45	0.38	0.43
2030	32.9	34.1	30.6	33.3	26.8	33.3	32.4	33.3	31.5	32.4	0.44	0.48	0.40	0.45	0.59	0.45	0.42	0.45	0.38	0.43
2031	37.6	37.9	35.1	37.9	37.1	37.9	32.3	38.0	36.7	37.4	0.47	0.49	0.42	0.48	0.57	0.48	0.41	0.48	0.40	0.47
2032	41.4	41.7	38.9	41.7	41.9	41.7	31.8	41.9	36.0	41.1	0.48	0.49	0.44	0.48	0.57	0.48	0.40	0.49	0.39	0.47
2033	40.7	40.8	38.1	40.9	41.1	40.9	31.0	41.2	38.0	40.5	0.47	0.47	0.43	0.47	0.52	0.47	0.38	0.48	0.40	0.47
2034	41.8	41.2	39.4	42.0	41.3	42.0	33.1	42.1	38.0	41.9	0.45	0.45	0.41	0.45	0.46	0.45	0.38	0.45	0.38	0.45
2035	43.8	44.6	41.3	44.1	43.8	44.1	34.2	44.1	39.9	43.9	0.44	0.45	0.41	0.45	0.45	0.45	0.38	0.45	0.39	0.44
2036	45.0	45.8	41.8	45.2	44.0	45.2	32.0	45.1	42.1	45.1	0.43	0.44	0.39	0.43	0.43	0.43	0.35	0.43	0.39	0.43
2037	47.4	48.6	43.2	47.7	43.3	47.7	30.9	47.7	44.1	47.4	0.44	0.45	0.39	0.44	0.41	0.44	0.34	0.44	0.40	0.44
2038	55.4	55.2	50.5	55.7	43.4	55.7	30.1	55.9	54.0	55.3	0.47	0.47	0.41	0.47	0.40	0.47	0.32	0.47	0.44	0.47
2039	44.3	45.8	38.9	44.6	42.3	44.6	29.7	44.9	40.7	44.0	0.42	0.43	0.35	0.43	0.41	0.43	0.32	0.43	0.37	0.42
2040	51.2	52.7	45.3	51.6	44.5	51.6	29.3	52.0	46.6	51.0	0.46	0.46	0.39	0.46	0.42	0.46	0.32	0.46	0.41	0.45
2041	52.3	53.5	45.7	52.9	45.7	52.9	30.7	53.4	45.4	51.9	0.46	0.47	0.38	0.47	0.42	0.47	0.33	0.47	0.38	0.46
2042	60.9	61.3	53.6	61.5	47.6	61.6	33.4	62.2	53.4	60.1	0.50	0.50	0.41	0.51	0.43	0.51	0.35	0.51	0.44	0.49
2043	63.9	64.7	55.6	64.6	50.6	64.7	42.7	65.5	62.3	63.0	0.51	0.51	0.41	0.52	0.44	0.52	0.41	0.52	0.46	0.50
2044	56.8	58.7	44.6	57.3	52.3	57.3	41.3	58.4	50.3	55.8	0.49	0.50	0.36	0.50	0.47	0.50	0.40	0.50	0.40	0.48
2045	61.3	63.1	49.2	61.8	53.2	61.9	41.5	62.6	55.1	59.9	0.51	0.51	0.38	0.52	0.46	0.52	0.40	0.51	0.42	0.50
2046	63.6	65.3	53.0	63.8	56.0	63.9	48.4	64.6	49.3	62.2	0.52	0.52	0.39	0.52	0.49	0.52	0.45	0.52	0.39	0.51
2047	64.6	66.8	48.6	64.7	58.1	64.7	51.4	65.6	48.7	63.3	0.55	0.55	0.37	0.55	0.53	0.55	0.48	0.55	0.39	0.54
2048	68.4	71.3	42.8	69.1	63.8	69.2	49.5	70.6	50.1	66.4	0.55	0.55	0.34	0.55	0.54	0.55	0.47	0.55	0.40	0.54
2049	65.6	69.4	40.4	66.6	61.3	66.6	49.2	68.3	51.0	63.5	0.55	0.56	0.32	0.56	0.56	0.56	0.48	0.56	0.41	0.54
2050	69.4	72.4	43.4	70.3	66.6	70.3	55.6	72.1	51.2	68.2	0.56	0.57	0.34	0.57	0.58	0.57	0.52	0.57	0.41	0.56
Mean	46.5	47.9	39.3	46.8	37.6	46.8	36.4	47.2	39.7	46.5	0.49	0.53	0.41	0.50	0.52	0.50	0.43	0.50	0.40	0.49

Table 4: Error metrics of the persistence forecast (*Naive24*). Unlike in a usual electricity price forecasting context, this simple approach performs very poorly with MAPEs (averaged over all simulated years) ranging between 0.40 and 0.53 for the different countries.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.4	2.6	5.3	7.9	5.2	12.7	5.6	3.1	7.4	0.14	0.21	0.08	0.14	0.40	0.14	0.26	0.14	0.09	0.17
2021	4.2	7.3	3.6	4.2	7.8	4.2	9.1	4.6	4.2	6.1	0.10	0.20	0.09	0.10	0.40	0.10	0.19	0.11	0.11	0.14
2022	4.2	7.7	4.0	4.2	8.3	4.2	11.3	4.5	3.3	6.9	0.10	0.20	0.10	0.10	0.42	0.10	0.21	0.10	0.08	0.15
2023	6.4	9.8	6.3	6.4	9.3	6.4	10.5	6.5	6.9	8.1	0.13	0.24	0.13	0.13	0.45	0.13	0.19	0.13	0.15	0.16
2024	20.5	20.3	18.8	20.4	13.5	20.4	9.8	18.8	18.5	21.0	0.31	0.38	0.29	0.31	0.54	0.31	0.17	0.29	0.29	0.32
2025	17.4	21.7	18.3	17.1	14.0	16.1	8.1	17.8	18.1	18.3	0.24	0.32	0.26	0.24	0.54	0.23	0.14	0.25	0.25	0.25
2026	13.2	16.3	13.3	13.2	13.9	13.2	8.1	14.0	14.7	13.8	0.20	0.26	0.20	0.21	0.52	0.21	0.14	0.22	0.22	0.21
2027	12.8	15.4	12.3	12.8	13.9	12.9	8.7	12.2	14.1	13.0	0.21	0.27	0.20	0.22	0.62	0.22	0.14	0.21	0.22	0.22
2028	8.9	11.1	7.9	9.0	12.7	9.1	7.9	8.7	9.1	9.0	0.14	0.19	0.13	0.15	0.51	0.15	0.13	0.14	0.14	0.15
2029	11.3	13.6	10.1	11.5	14.7	11.6	8.5	11.2	10.3	11.7	0.17	0.22	0.15	0.18	0.50	0.18	0.13	0.17	0.15	0.18
2030	12.8	14.8	11.4	13.1	17.7	13.2	9.0	12.9	11.7	13.0	0.19	0.23	0.16	0.19	0.42	0.20	0.13	0.19	0.16	0.19
2031	15.9	17.5	14.4	16.0	21.7	16.1	9.1	16.1	16.1	16.0	0.21	0.25	0.19	0.22	0.36	0.22	0.13	0.22	0.19	0.22
2032	19.9	20.5	18.1	20.0	22.7	20.4	9.8	20.6	17.3	19.4	0.24	0.26	0.22	0.25	0.33	0.25	0.14	0.25	0.20	0.24
2033	17.1	18.2	15.1	17.2	19.9	16.6	11.4	17.1	16.3	16.3	0.20	0.22	0.18	0.21	0.26	0.20	0.15	0.20	0.18	0.20
2034	17.4	17.7	16.5	18.1	18.8	18.1	10.7	18.0	16.6	17.9	0.20	0.20	0.19	0.21	0.23	0.21	0.14	0.20	0.18	0.20
2035	22.3	23.1	21.0	21.6	22.4	21.0	14.6	21.5	20.2	22.0	0.23	0.24	0.22	0.23	0.24	0.22	0.17	0.23	0.20	0.23
2036	19.7	17.9	18.1	19.5	19.2	18.9	11.7	20.1	18.2	19.8	0.20	0.18	0.18	0.20	0.20	0.19	0.14	0.20	0.18	0.20
2037	19.9	18.7	19.2	19.9	17.7	18.0	12.8	19.5	18.8	20.0	0.19	0.18	0.18	0.19	0.18	0.17	0.15	0.19	0.17	0.19
2038	23.5	21.0	20.0	22.9	19.6	22.5	15.3	23.8	22.7	23.3	0.21	0.19	0.17	0.21	0.19	0.20	0.18	0.21	0.20	0.21
2039	21.8	22.4	19.9	22.7	16.7	22.3	13.5	21.8	19.1	22.5	0.22	0.22	0.19	0.23	0.17	0.22	0.16	0.22	0.18	0.22
2040	20.2	19.5	18.9	20.4	18.6	19.1	13.0	20.5	19.8	18.9	0.19	0.19	0.17	0.19	0.19	0.18	0.15	0.19	0.18	0.18
2041	19.8	21.3	17.5	20.5	18.5	20.1	11.8	19.7	19.5	19.4	0.19	0.20	0.16	0.20	0.19	0.19	0.14	0.19	0.18	0.19
2042	25.4	25.0	22.2	25.2	20.8	23.9	13.0	25.9	24.4	24.2	0.22	0.22	0.18	0.22	0.20	0.21	0.15	0.23	0.21	0.22
2043	22.2	22.9	21.3	20.4	22.2	19.5	18.9	21.8	23.9	22.6	0.19	0.20	0.17	0.18	0.21	0.17	0.20	0.19	0.19	0.20
2044	21.9	23.2	22.8	19.9	19.7	19.8	16.8	21.4	23.1	21.9	0.21	0.22	0.20	0.19	0.19	0.19	0.18	0.20	0.20	0.21
2045	22.4	24.9	24.7	22.4	21.9	22.0	21.4	23.0	24.1	23.2	0.20	0.22	0.20	0.20	0.21	0.20	0.22	0.21	0.20	0.21
2046	26.5	26.4	27.6	23.1	22.9	23.3	25.4	25.9	15.7	26.5	0.24	0.23	0.22	0.21	0.22	0.21	0.26	0.23	0.14	0.24
2047	19.3	20.3	21.6	18.6	21.5	18.8	21.5	19.2	14.2	20.8	0.18	0.19	0.18	0.18	0.22	0.18	0.22	0.18	0.13	0.20
2048	29.6	31.2	20.0	28.5	25.8	28.9	26.4	28.9	14.5	30.9	0.26	0.27	0.17	0.25	0.25	0.26	0.27	0.25	0.13	0.28
2049	18.7	20.9	16.8	18.4	21.8	17.6	22.3	19.9	14.3	19.6	0.17	0.19	0.15	0.17	0.22	0.16	0.23	0.18	0.13	0.18
2050	21.0	25.1	17.4	21.2	22.0	21.0	25.4	22.4	15.4	24.9	0.19	0.22	0.15	0.19	0.22	0.19	0.26	0.20	0.14	0.23
Mean	17.5	18.8	16.2	17.2	17.7	16.9	13.8	17.5	15.7	18.0	0.20	0.23	0.18	0.20	0.32	0.19	0.18	0.20	0.17	0.21

Table 5: Error metrics of the approach using multiple linear regression with a multinominal logistic regression classifier (LRw/C). With MAPEs ranging from 0.17 to 0.32, this approach clearly outperforms the naive approach. Please note that the results are strongly affected by very few wrongly classified outlier prices. Thus, Table 10 in Appendix A additionally presents the results with the 0.25% worst forecasts in each country being removed from the data sets.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.9	3.9	5.1	3.5	5.3	10.3	5.8	6.1	7.4	0.13	0.23	0.11	0.13	0.18	0.14	0.22	0.15	0.17	0.17
2021	5.6	6.3	5.1	5.3	2.8	5.4	10.2	5.9	5.7	7.3	0.13	0.17	0.13	0.13	0.15	0.13	0.20	0.14	0.15	0.16
2022	5.9	6.3	6.3	6.1	3.5	6.1	12.2	6.1	7.2	8.0	0.13	0.16	0.15	0.14	0.18	0.14	0.23	0.14	0.17	0.17
2023	8.8	8.5	8.9	8.8	3.8	8.7	12.1	8.8	8.9	10.4	0.18	0.20	0.18	0.18	0.18	0.18	0.22	0.18	0.18	0.20
2024	21.6	16.9	20.2	21.7	7.3	21.5	10.3	20.8	21.2	22.6	0.33	0.31	0.31	0.33	0.29	0.32	0.18	0.32	0.33	0.33
2025	15.4	19.5	16.1	15.5	5.5	14.7	9.4	14.5	14.9	16.2	0.22	0.28	0.22	0.22	0.22	0.21	0.16	0.20	0.21	0.22
2026	14.5	16.0	15.9	15.4	5.7	16.6	9.9	14.7	17.2	16.5	0.22	0.26	0.25	0.24	0.21	0.26	0.17	0.23	0.25	0.25
2027	16.2	15.9	16.3	16.3	8.0	16.1	13.3	16.2	17.5	18.2	0.26	0.28	0.26	0.27	0.36	0.26	0.21	0.27	0.26	0.29
2028	11.0	19.4	18.7	9.4	4.8	11.5	15.0	11.2	14.9	9.8	0.19	0.35	0.31	0.16	0.20	0.20	0.24	0.19	0.23	0.16
2029	11.0	10.4	10.8	10.4	7.4	11.0	11.3	10.3	14.5	12.3	0.16	0.17	0.16	0.16	0.25	0.17	0.17	0.16	0.19	0.18
2030	9.7	9.3	8.9	8.6	16.1	9.4	8.6	8.6	14.1	10.6	0.14	0.15	0.13	0.13	0.39	0.14	0.13	0.13	0.18	0.16
2031	10.4	11.1	9.1	9.1	19.5	9.5	7.2	10.2	12.5	10.8	0.14	0.16	0.12	0.13	0.33	0.13	0.11	0.14	0.15	0.15
2032	11.0	13.3	10.4	9.6	13.0	10.7	9.0	11.7	13.8	10.6	0.14	0.17	0.13	0.12	0.19	0.14	0.13	0.15	0.17	0.13
2033	10.7	10.6	10.7	9.5	13.1	9.2	10.1	9.4	16.9	9.9	0.13	0.13	0.13	0.12	0.18	0.11	0.14	0.11	0.19	0.12
2034	10.7	11.0	12.2	11.4	13.6	11.9	8.8	13.6	17.9	12.1	0.13	0.13	0.14	0.13	0.17	0.14	0.12	0.16	0.19	0.14
2035	14.3	15.0	15.0	14.0	15.1	13.8	10.3	15.8	15.2	15.1	0.15	0.16	0.16	0.15	0.17	0.15	0.13	0.17	0.16	0.16
2036	12.7	13.5	14.9	13.9	14.4	12.1	9.1	15.4	13.5	12.9	0.13	0.14	0.15	0.14	0.15	0.13	0.11	0.16	0.14	0.13
2037	13.4	12.3	13.6	12.7	12.1	12.9	9.7	13.3	17.2	12.2	0.13	0.12	0.13	0.13	0.13	0.13	0.12	0.13	0.16	0.12
2038	15.3	14.8	15.3	14.7	11.8	12.7	7.4	14.9	16.6	14.4	0.14	0.14	0.14	0.14	0.12	0.12	0.09	0.14	0.15	0.13
2039	14.1	17.0	13.2	15.1	11.4	14.1	7.4	12.9	15.8	14.8	0.15	0.18	0.13	0.16	0.12	0.14	0.09	0.13	0.15	0.15
2040	11.7	12.0	12.0	11.0	9.1	10.4	7.4	12.4	13.2	10.3	0.11	0.12	0.11	0.11	0.10	0.10	0.09	0.12	0.13	0.10
2041	19.1	17.6	21.9	20.1	20.9	17.4	10.8	17.7	15.3	19.3	0.18	0.17	0.19	0.19	0.20	0.16	0.12	0.17	0.14	0.18
2042	21.8	22.2	20.9	20.3	19.5	20.2	13.1	22.5	19.9	20.3	0.19	0.19	0.17	0.18	0.19	0.18	0.15	0.20	0.17	0.18
2043	31.8	36.0	35.2	31.2	36.0	31.9	25.3	34.8	34.3	28.9	0.27	0.31	0.28	0.27	0.33	0.28	0.26	0.30	0.28	0.25
2044	18.0	18.7	22.7	15.3	16.1	16.7	12.3	20.1	20.9	21.9	0.17	0.18	0.20	0.15	0.16	0.16	0.13	0.19	0.19	0.21
2045	16.3	18.5	18.7	15.6	18.9	13.8	16.7	14.8	18.1	18.2	0.15	0.16	0.15	0.14	0.18	0.13	0.17	0.13	0.15	0.17
2046	22.5	26.3	24.6	26.2	19.0	20.8	20.0	28.9	36.8	23.4	0.21	0.24	0.20	0.24	0.19	0.19	0.21	0.26	0.32	0.22
2047	14.0	15.3	16.8	12.5	16.5	13.4	15.0	14.4	18.2	14.4	0.13	0.14	0.14	0.12	0.17	0.13	0.16	0.14	0.16	0.14
2048	30.8	33.8	19.2	31.9	39.9	29.0	27.5	30.7	58.5	31.0	0.27	0.29	0.16	0.28	0.38	0.25	0.27	0.27	0.50	0.28
2049	16.4	25.8	17.5	13.8	17.4	18.4	17.2	17.6	16.3	15.0	0.15	0.23	0.15	0.13	0.18	0.17	0.18	0.16	0.15	0.14
2050	15.7	20.5	10.7	17.7	15.8	13.9	21.0	19.6	26.9	15.3	0.14	0.18	0.09	0.16	0.16	0.13	0.22	0.18	0.23	0.15
Mean	14.7	16.2	15.0	14.5	13.6	14.2	12.5	15.3	18.1	15.2	0.17	0.20	0.17	0.17	0.21	0.17	0.17	0.18	0.20	0.18

Table 6: Error metrics of the approach using a feedforward neural network with a feedforward neural network classifier (*ANNw/C*). With MAPEs ranging from 0.17 to 0.21, this approach clearly outperforms both, the naive approach and the linear regression. Please note that the results are strongly affected by very few wrongly classified outlier prices. Thus, Table 11 in Appendix A additionally presents the results with the 0.25% worst forecasts in each country being removed from the data sets.

The first thing to observe is that the MAEs increase over the course of the simulation for all forecasting approaches considered. However, this finding is mostly related to the general increase of the price level as previously mentioned and shown in the subsequent Section 4.3. Thus, it is reasonable to focus on the MAPEs instead, which remain more stable throughout the simulation period.

Moreover, we find that unlike in a usual electricity price forecasting context, the naive method (*Naive24*) performs very poorly with MAPEs (averaged over all simulated years) ranging between 0.40 and 0.53 for the different countries. This important result is due to the mutual dependencies between price forecasts and simulated prices as described in Section 3.1.2, such that no stable outcome can be achieved. The linear regression approach (*LRw/C*) and the ANN approach (*ANNw/C*), both equipped with an additional classifier, clearly outperform the naive approach with MAPEs ranging from 0.17 to 0.32 and 0.17 and 0.21, respectively.

Please note, however, that these results are strongly affected by very few wrongly classified outlier prices. To show this, we additionally remove the 0.25% worst forecasts of each approach and for each country and recalculate the MAEs and MAPEs for the remaining 99.75% of the forecasted prices. The results for all five approaches are shown in Tables 9–13 in Appendix A. We can observe that, although only very few data points have been removed, the error metrics improve substantially. The adjusted MAPE for the *ANNw/C* approach decreases to values between 0.12 and 0.16 for the different countries, and the *LRw/C* approach improves to values between 0.13 and 0.26. Given the complex dynamic setup with several mutual dependencies, we therefore consider the forecasts of the *ANNw/C* approach to be sufficiently accurate.

Regarding the benefit of using an additional classifier, we can state that this is much more relevant for the linear regression than for the ANN. This finding is rather straightforward: While the ANN approach is capable of handling outlier prices quite well even without a classifier, the linear regression approach is strongly distorted when fit to data sets including few, but extreme outliers. This is because not the entire value space is covered by observations and linear relationships fail to replicate large variations in the dependent variable with only moderate variations in explaining variables. For the detailed results of the approaches without classifier, please refer to Appendix A.

What remains to be proven is whether the differences between the forecasting approaches are statistically significant. For this purpose, Fig. 7 presents the results of the Diebold-Mariano tests, which allow us to assess whether there is a clear rank of the approaches. We find the *ANNw/C* method to outperform both, the *LRw/C* approach and the *Naive24* approach, at a very strong significance level $p \leq 0.01$. Moreover, *LRw/C* is superior to *Naive24*, also at a significance level $p \leq 0.01$. The

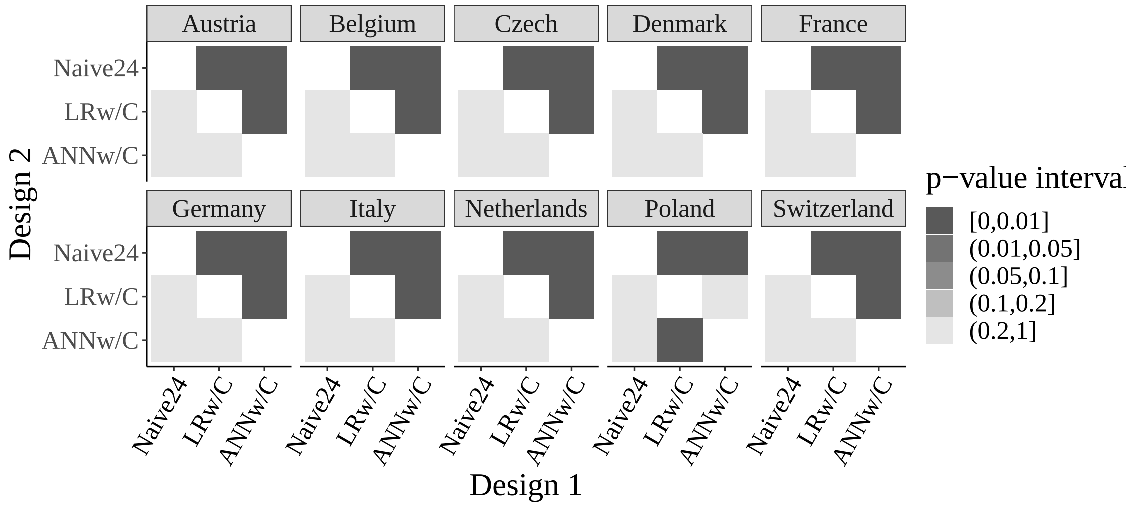


Figure 7: Results of the Diebold-Mariano tests conducted to evaluate the statistical significance of the superiority of one forecasting approach over another. Reading example: *ANNw/C* (Design 1) is superior to *Naive24* (Design 2) in all countries at a significance level $p \leq 0.01$ as depicted by the respective grey tone.

only exception from these results is Poland, where LRw/C is able to outperform $ANNw/C$.

When it comes to the benefit of the additional classifier, the Diebold-Mariano tests confirm the previously described findings (see Fig. 9 in Appendix A): While the linear regression with classifier (LRw/C) clearly outperforms the approach without classifier (LRw/oC) in all considered countries (significance level $p \leq 0.01$, as before), this does not apply for the ANN approach. However, also the ANN approach with classifier ($ANNw/C$) is statistically significantly better than the one without classifier ($ANNw/oC$) in six out of ten countries, with one draw (no significantly better approach in Switzerland) and three defeats. Thus, while the focus of our paper is not on whether or not classifiers should be used, we can still state that the practice of doing so seems leads to preferable outcomes. Yet, the use of a classifier is clearly much more relevant when working with linear rather than non-linear approaches.

4.3 Impact of Forecasting Accuracy on Market Outcomes

Instead of solely focusing on the forecasting performance, we now want to inspect another key aspect of model-endogenous price forecasting: the impact on the eventual market outcomes of the simulation. For this purpose, Fig. 8 shows the development of the volume-weighted average prices in all simulated market areas.

Firstly, we can observe a notable increase of the general price level as the simulation moves on. This is related to the model assumptions described in Section 4.1, most notably the assumed increase of the carbon price to $150\,\mathrm{EUR/t_{CO_2}}$ in 2050 with 20% of the electricity demand remaining to be covered by non-renewable generation in this year.

Secondly, however, we can also observe that the price curves of the *LRw/C* and the *ANNw/C* approaches appear to be quite similar, while the price level using the *Naive24* method is elevated. This is an important finding as it directly highlights the crucial importance of sufficiently accurate model-endogenous price forecasts in ABMs of electricity markets. Otherwise, distorted bidding behavior may occur, e.g., if agents incorrectly assume that start-up costs occur and integrate these into their bids. Ultimately, this may result in distorted market outcomes. In that sense, the prices simulated under the more accurate price forecasts can be expected to be closer to reality, since real-world electricity price forecasting is a very advanced field with high levels of accuracy. This aspect is crucial, since simulated day-ahead market electricity prices are typically one of the major results of electricity market models.

An interesting side result of our analyses is that we indirectly confirm the statement of Ghoddusi et al. (2019), who claim that real-world electricity markets have already become much more efficient through the use of more sophisticated price forecasting methods. Thus, the benefit of increasing forecasting performance even further may be limited.

Yet, our most important finding is that while ANN approaches are found to be very useful in the context of ABMs and are increasing the quality and reliability of the model results, simpler approaches, e.g., based on linear regression, can be considered as a feasible alternative in future work. In our particular case, a linear regression with logistic classifier, too, performs reasonably well (only slightly worse than the ANN), but reduces the computational time required for the price forecasts by roughly 60% as compared to the ANN approach.

5 Conclusion and Outlook

In this article, we developed an electricity price forecasting technique using artificial neural networks and successfully integrated the novel approach into the established agent-based electricity market simulation model PowerACE. Our proposed methodology combines the fields of machine learning and agent-based modeling, both of

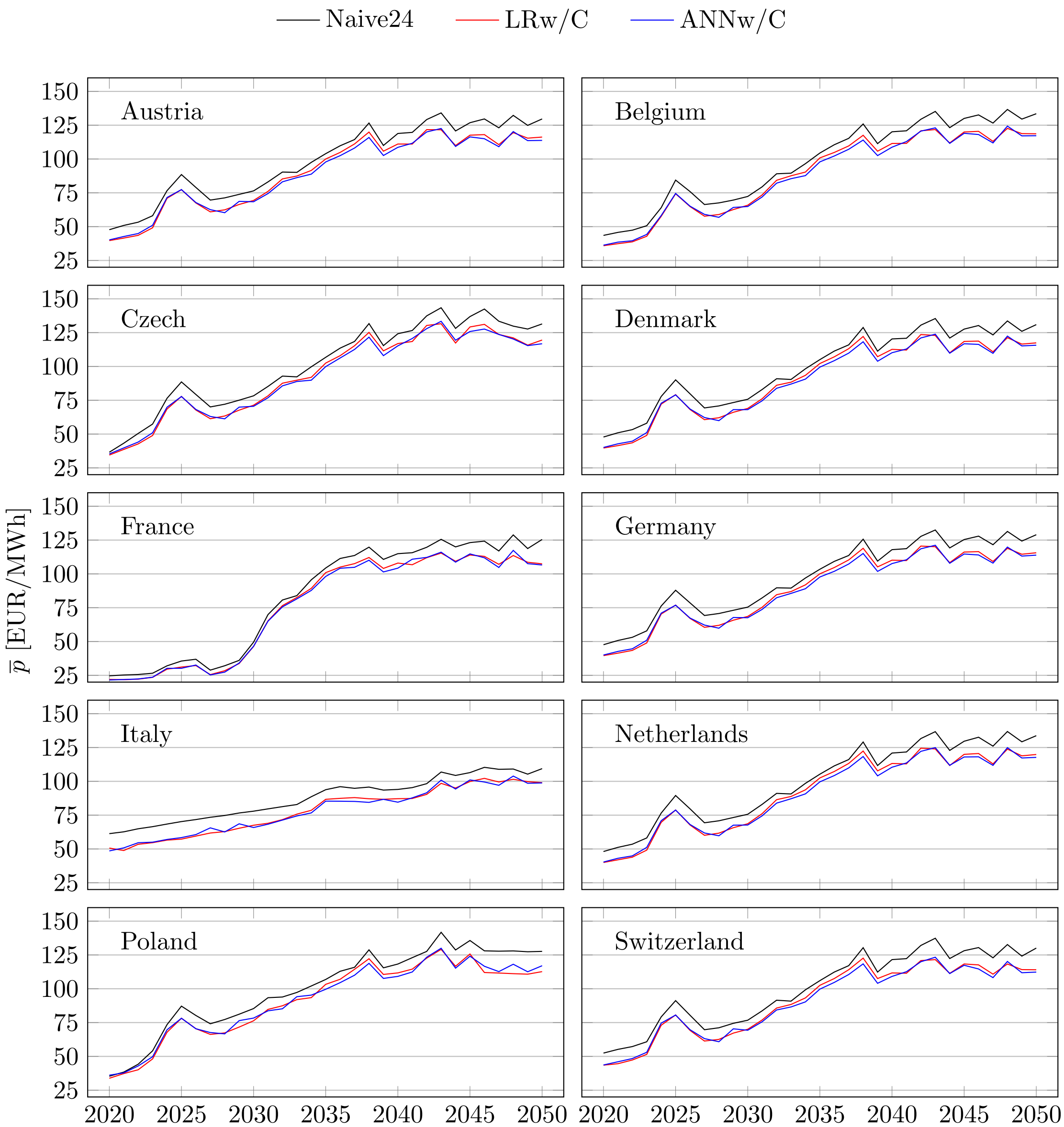


Figure 8: Simulated development of the volume-weighted average day-ahead prices. Due to model assumptions like an increase of the carbon price to $150\,\mathrm{EUR/t_{CO_2}}$ in 2050, the price level generally rises strongly. However, also a strong impact of the price forecasting approach can be observed. The persistence forecast (*Naive24*) clearly leads to higher simulated prices than the other two approaches, which highlights the crucial importance of forecasting accuracy.

which are very popular in the field of energy research.

In a case study covering ten interconnected European countries and a time horizon from 2020 until 2050 at hourly resolution, we benchmarked the new forecasting approach against a more simple linear regression model as well as a naive persistence forecast. Using Diebold-Mariano hypothesis tests, we then evaluated the statistical significance of the superiority of one approach over another. The major results of our simulations can be summarized as follows. Firstly, in contrast to real-world electricity price forecasts, we found naive approaches to perform very poorly when deployed model-endogenously in an agent-based framework. Secondly, although the linear regression performs reasonably well, it is outperformed by the neural network approach, which we could prove with strong statistical significance. Thirdly, the use of an additional classifier for outlier handling substantially improves the forecasting accuracy, particularly when linear approaches are deployed. Fourthly, the choice of the model-endogenous forecasting method has a clear impact on simulated electricity prices, which is crucial since these prices are a major results of electricity market models. Please note that this finding does not only apply to our particular simulation model, but is relevant for any agent-based approach in the field of electricity market simulation that relies on a price forecast to define agents' actions.

On the one hand, we can conclude that despite the superiority of the neural network approach, less computationally expensive approaches, e.g., based on linear regression, should always be considered as an alternative. If well fit to the scope, such approaches may – as in our particular case – come close to the accuracy of more advanced methods, yet at a much lower computational burden.

However, on the other hand, we are also well aware that far more sophisticated types of neural networks exist than simple feedforward networks we used. While the objective of our study was mostly on showing the potential of integrating neural networks into an agent-based modeling framework, we can well imagine that more advanced methods may bring additional benefits. In particular, recurrent neural networks may help to better account for time dependencies caused by electricity storage. Yet, the trade-off between accuracy and computational performance always needs to be considered.

Although our analysis focused on one particular field of application, we also see great potential in the joint application of methods from machine learning and agent-based modeling in other research contexts. Thus, we hope that our paper serves as a starting point and encourages fellow researchers to adapt our approach to their respective field of application.

Acknowledgments

The authors acknowledge the financial support of the German Federal Ministry of Education and Research under grant number 03SFK1F0-2 (ENSURE – Neue Energienetzstrukturen für die Energiewende).

A Additional Results

Tables 7 and 8 show the MAEs and MAPEs in all countries and years for the linear regression approach without classifier (*LRw/oC*) and the ANN approach without classifier (*ANNw/oC*), respectively. In Fig. 9, the results of the Diebold-Mariano tests are depicted for all investigated forecasting approaches. Moreover, in Tables 9–13, adjusted MAEs and MAPEs with the 0.25% worst forecasts per country and approach being filtered are presented. This highlights the strong impact of few wrongly classified extreme outlier prices.

References

Adya, M., Collopy, F., 1998. How effective are neural networks at forecasting and prediction? A review and evaluation. Journal of Forecasting 17, 481–495.

Bento, P., Pombo, J., Calado, M., Mariano, S., 2018. A bat optimized neural network and wavelet transform approach for short-term price forecasting. Applied Energy 210, 88–97. doi:10.1016/j.apenergy.2017.10.058.

Bublitz, A., Keles, D., Zimmermann, F., Fraunholz, C., Fichtner, W., 2019. A survey on electricity market design: Insights from theory and real-world implementations of capacity remuneration mechanisms. Energy Economics 80, 1059–1078. doi:10.1016/j.eneco.2019.01.030.

Catalão, J., Mariano, S., Mendes, V., Ferreira, L., 2007. Short-term electricity prices forecasting in a competitive market: A neural network approach. Electric Power Systems Research 77, 1297–1304. doi:10.1016/j.epsr.2006.09.022.

Chappin, E.J., de Vries, L.J., Richstein, J.C., Bhagwat, P., Iychettira, K., Khan, S., 2017. Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab). Environmental Modelling & Software 96, 421–431. doi:10.1016/j.envsoft.2017.07.009.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.4	2.6	5.3	7.9	5.2	12.7	5.6	3.1	7.4	0.14	0.21	0.08	0.14	0.40	0.14	0.26	0.14	0.09	0.17
2021	4.2	7.3	3.6	4.2	7.8	4.2	9.1	4.6	4.2	6.1	0.10	0.20	0.09	0.10	0.40	0.10	0.19	0.11	0.11	0.14
2022	4.2	7.7	4.0	4.2	8.3	4.2	11.3	4.5	3.3	6.9	0.10	0.20	0.10	0.10	0.42	0.10	0.21	0.10	0.08	0.15
2023	6.4	9.8	6.3	6.4	9.3	6.4	10.5	6.5	6.9	8.1	0.13	0.24	0.13	0.13	0.45	0.13	0.19	0.13	0.15	0.16
2024	40.2	31.4	36.6	40.0	16.1	40.1	8.8	38.5	37.7	39.0	0.58	0.58	0.54	0.58	0.66	0.58	0.16	0.57	0.54	0.57
2025	59.4	52.9	58.4	59.4	18.0	59.4	8.6	56.6	59.9	59.3	0.79	0.74	0.78	0.79	0.73	0.79	0.15	0.76	0.77	0.79
2026	39.2	37.4	39.1	38.9	20.5	38.9	8.4	38.5	40.0	39.1	0.59	0.59	0.58	0.59	0.78	0.59	0.14	0.58	0.56	0.58
2027	10.3	12.0	9.8	10.3	13.3	10.3	8.6	10.1	11.7	10.4	0.18	0.22	0.17	0.18	0.59	0.18	0.14	0.18	0.19	0.18
2028	9.7	11.7	8.6	9.8	12.9	9.9	8.6	9.5	10.1	9.7	0.16	0.20	0.14	0.16	0.51	0.16	0.14	0.15	0.15	0.16
2029	11.9	13.8	10.4	12.0	14.0	12.1	8.9	11.9	11.2	12.1	0.18	0.23	0.16	0.19	0.48	0.19	0.14	0.19	0.16	0.19
2030	13.7	15.1	11.9	13.9	16.8	13.9	9.7	13.7	12.5	13.7	0.20	0.24	0.17	0.21	0.40	0.21	0.14	0.20	0.17	0.20
2031	19.2	19.3	17.7	19.2	21.1	19.3	9.5	19.2	19.3	18.2	0.26	0.28	0.24	0.26	0.36	0.27	0.14	0.26	0.23	0.25
2032	34.6	34.5	34.1	34.4	31.5	34.6	10.6	34.5	24.4	32.8	0.42	0.43	0.40	0.42	0.46	0.42	0.15	0.42	0.28	0.41
2033	39.1	39.0	38.5	38.8	36.9	38.9	17.2	39.0	33.9	37.4	0.46	0.46	0.44	0.46	0.49	0.46	0.22	0.46	0.37	0.44
2034	42.6	41.2	39.1	42.6	41.3	42.7	20.5	42.7	35.8	42.1	0.48	0.47	0.43	0.48	0.49	0.48	0.25	0.48	0.38	0.47
2035	55.3	55.1	53.8	55.9	53.9	56.0	33.3	56.0	47.8	55.0	0.56	0.56	0.53	0.57	0.57	0.57	0.38	0.57	0.46	0.56
2036	58.8	58.0	58.6	59.4	56.9	59.5	31.5	59.5	52.3	58.5	0.58	0.57	0.56	0.58	0.58	0.59	0.35	0.58	0.49	0.57
2037	69.0	65.4	69.1	69.0	59.7	69.1	33.1	69.0	61.2	68.6	0.64	0.62	0.62	0.64	0.59	0.64	0.36	0.64	0.55	0.64
2038	80.2	76.2	82.2	80.1	61.0	80.1	15.6	80.2	79.2	79.5	0.70	0.68	0.68	0.71	0.58	0.71	0.19	0.70	0.65	0.70
2039	65.0	62.7	65.1	64.6	52.4	64.8	16.7	65.0	61.8	63.5	0.62	0.60	0.58	0.62	0.52	0.62	0.19	0.62	0.55	0.61
2040	64.9	64.4	64.2	64.6	53.0	64.8	17.7	65.0	52.7	61.8	0.59	0.59	0.55	0.59	0.52	0.59	0.20	0.59	0.47	0.57
2041	62.8	63.1	62.4	62.0	51.0	62.1	17.6	62.5	50.3	58.5	0.58	0.58	0.53	0.58	0.50	0.58	0.20	0.58	0.44	0.55
2042	71.7	71.2	73.2	71.4	55.3	71.5	20.8	71.9	56.3	67.0	0.61	0.60	0.57	0.61	0.51	0.61	0.22	0.61	0.46	0.58
2043	77.8	77.3	80.6	77.9	61.5	78.0	37.0	78.5	73.4	75.9	0.66	0.65	0.62	0.67	0.57	0.67	0.36	0.66	0.56	0.65
2044	58.5	58.5	50.8	57.4	49.3	57.5	32.3	58.5	43.1	56.2	0.54	0.53	0.43	0.54	0.47	0.54	0.33	0.54	0.37	0.52
2045	60.9	62.3	55.8	60.4	53.3	60.5	38.7	61.2	47.3	57.8	0.52	0.53	0.43	0.52	0.48	0.53	0.37	0.52	0.37	0.51
2046	68.7	70.1	66.6	68.9	62.3	69.0	47.4	69.8	23.9	67.0	0.60	0.60	0.52	0.61	0.58	0.61	0.46	0.61	0.21	0.60
2047	53.0	54.1	44.5	52.2	48.0	52.3	41.0	53.1	16.6	50.2	0.48	0.48	0.36	0.48	0.47	0.48	0.40	0.48	0.15	0.46
2048	75.2	78.1	30.3	75.7	68.2	75.8	52.7	77.7	18.2	72.4	0.65	0.66	0.25	0.66	0.65	0.66	0.52	0.66	0.16	0.65
2049	63.6	65.1	16.4	63.2	54.2	63.1	44.6	64.5	19.0	57.1	0.58	0.57	0.15	0.57	0.54	0.57	0.45	0.57	0.17	0.53
2050	55.3	59.0	16.5	56.5	52.6	57.0	44.5	57.7	20.4	55.1	0.49	0.51	0.14	0.50	0.52	0.50	0.44	0.50	0.18	0.50
Mean	44.5	44.5	39.1	44.5	37.7	44.6	22.2	44.7	33.5	43.4	0.46	0.47	0.39	0.46	0.52	0.46	0.26	0.46	0.34	0.45

Table 7: Error metrics of the approach using multiple linear regression without classifier (*LRw/oC*). This approach performs much worse than the corresponding one with classifier (*LRw/C*, cf. Table 5), because the linear regression approach is strongly distorted when fit to data sets including few, but extreme outliers.

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.2	7.9	3.9	5.1	3.5	5.3	10.3	5.8	6.1	7.4	0.13	0.23	0.11	0.13	0.18	0.14	0.22	0.15	0.17	0.17
2021	5.6	6.3	5.1	5.3	2.8	5.4	10.2	5.9	5.7	7.3	0.13	0.17	0.13	0.13	0.15	0.13	0.20	0.14	0.15	0.16
2022	5.9	6.3	6.3	6.1	3.5	6.1	12.2	6.1	7.2	8.0	0.13	0.16	0.15	0.14	0.18	0.14	0.23	0.14	0.17	0.17
2023	8.8	8.5	8.9	8.8	3.8	8.7	12.1	8.8	8.9	10.4	0.18	0.20	0.18	0.18	0.18	0.18	0.22	0.18	0.18	0.20
2024	21.2	19.8	24.6	22.2	11.2	21.4	10.7	20.5	22.0	23.7	0.32	0.36	0.38	0.33	0.44	0.32	0.19	0.32	0.34	0.35
2025	11.8	14.5	12.6	12.7	6.5	12.3	8.6	11.2	15.7	14.2	0.17	0.22	0.18	0.18	0.26	0.18	0.15	0.16	0.22	0.20
2026	14.9	15.0	16.5	16.2	8.0	15.9	11.1	15.6	18.0	17.2	0.23	0.24	0.25	0.25	0.30	0.24	0.18	0.24	0.26	0.26
2027	13.6	13.7	14.4	14.6	8.1	13.5	10.0	13.4	15.2	14.9	0.23	0.25	0.24	0.25	0.37	0.23	0.16	0.23	0.24	0.25
2028	7.2	8.1	7.5	7.3	4.5	7.1	9.4	7.1	7.5	7.9	0.12	0.14	0.12	0.12	0.18	0.12	0.15	0.12	0.11	0.13
2029	7.9	8.9	8.7	7.4	7.6	7.8	8.6	7.6	7.8	9.2	0.13	0.15	0.13	0.12	0.26	0.12	0.13	0.12	0.11	0.14
2030	8.3	9.4	12.2	7.9	14.8	7.9	10.0	7.7	10.3	9.8	0.12	0.15	0.18	0.12	0.35	0.12	0.15	0.12	0.14	0.14
2031	8.6	11.3	17.3	9.6	16.6	9.4	9.2	9.3	14.6	10.8	0.12	0.17	0.24	0.14	0.28	0.13	0.14	0.13	0.18	0.15
2032	14.7	15.9	37.1	16.9	16.1	16.9	8.7	14.5	18.4	15.9	0.18	0.20	0.45	0.21	0.23	0.21	0.12	0.18	0.22	0.20
2033	10.1	9.5	39.5	11.8	11.4	12.2	6.2	9.9	13.4	11.0	0.12	0.12	0.47	0.14	0.16	0.15	0.09	0.12	0.15	0.13
2034	9.9	9.3	41.2	12.6	11.4	10.7	10.3	10.1	12.7	11.3	0.12	0.11	0.48	0.15	0.14	0.13	0.13	0.12	0.14	0.13
2035	15.1	14.3	56.6	15.5	12.8	13.7	8.9	13.9	16.4	15.5	0.16	0.16	0.60	0.17	0.15	0.15	0.11	0.15	0.17	0.17
2036	13.0	10.7	66.0	16.4	10.1	11.9	7.1	11.7	17.2	13.1	0.13	0.11	0.66	0.17	0.11	0.12	0.09	0.12	0.17	0.14
2037	15.9	13.9	85.0	16.8	9.2	16.1	10.2	14.5	21.1	15.4	0.16	0.14	0.79	0.16	0.10	0.16	0.12	0.14	0.20	0.15
2038	19.5	14.1	91.0	18.6	11.0	15.5	8.3	20.2	21.8	17.7	0.18	0.13	0.78	0.17	0.11	0.14	0.10	0.19	0.19	0.16
2039	21.6	19.5	68.9	22.9	13.5	21.2	7.7	23.8	23.7	22.1	0.22	0.20	0.64	0.23	0.14	0.22	0.09	0.24	0.22	0.23
2040	15.1	13.1	71.6	20.2	6.8	13.6	6.1	15.5	19.3	14.2	0.15	0.13	0.64	0.20	0.07	0.13	0.07	0.15	0.18	0.14
2041	18.0	17.4	77.4	18.6	12.4	16.7	10.2	17.7	17.7	17.4	0.17	0.17	0.67	0.18	0.13	0.16	0.12	0.17	0.16	0.17
2042	20.6	16.6	77.7	20.6	12.9	18.4	12.9	20.4	21.5	18.8	0.19	0.15	0.63	0.19	0.13	0.17	0.14	0.18	0.19	0.17
2043	24.0	18.0	67.0	23.9	18.3	23.9	24.4	26.5	28.5	21.9	0.21	0.16	0.53	0.21	0.18	0.21	0.25	0.24	0.24	0.20
2044	21.9	19.8	29.2	23.6	14.2	17.6	17.9	23.0	24.1	16.8	0.21	0.19	0.26	0.23	0.14	0.17	0.20	0.22	0.21	0.16
2045	20.0	17.6	29.1	21.2	15.1	16.6	19.1	20.8	23.9	16.0	0.18	0.16	0.23	0.19	0.14	0.15	0.20	0.19	0.20	0.15
2046	26.7	21.6	34.7	31.4	21.2	23.7	25.2	26.2	24.4	19.4	0.24	0.19	0.28	0.29	0.20	0.22	0.26	0.23	0.21	0.18
2047	21.5	18.0	23.1	20.2	16.4	16.9	20.1	20.4	19.7	17.5	0.21	0.17	0.19	0.19	0.17	0.16	0.21	0.19	0.18	0.17
2048	29.8	25.6	34.6	35.7	28.4	25.4	26.8	27.1	21.9	27.9	0.26	0.22	0.28	0.31	0.27	0.22	0.27	0.23	0.20	0.25
2049	25.8	21.7	19.3	23.8	21.4	18.8	21.4	23.5	20.3	20.1	0.24	0.19	0.17	0.22	0.22	0.17	0.22	0.21	0.18	0.19
2050	25.1	20.4	18.4	18.8	21.2	17.4	23.8	21.8	21.6	19.7	0.23	0.18	0.15	0.17	0.21	0.16	0.25	0.19	0.19	0.18
Mean	15.7	14.4	35.7	16.5	12.1	14.4	12.8	15.5	17.0	15.2	0.18	0.18	0.36	0.19	0.20	0.17	0.17	0.18	0.19	0.18

Table 8: Error metrics of the approach using a feedforward neural network without classifier (*ANNw/oC*). This approach performs only slightly worse than the corresponding one with classifier (*ANNw/C*, cf. Table 6), because the non-linear character of the ANN allows to account for outliers relatively well even without classifier.

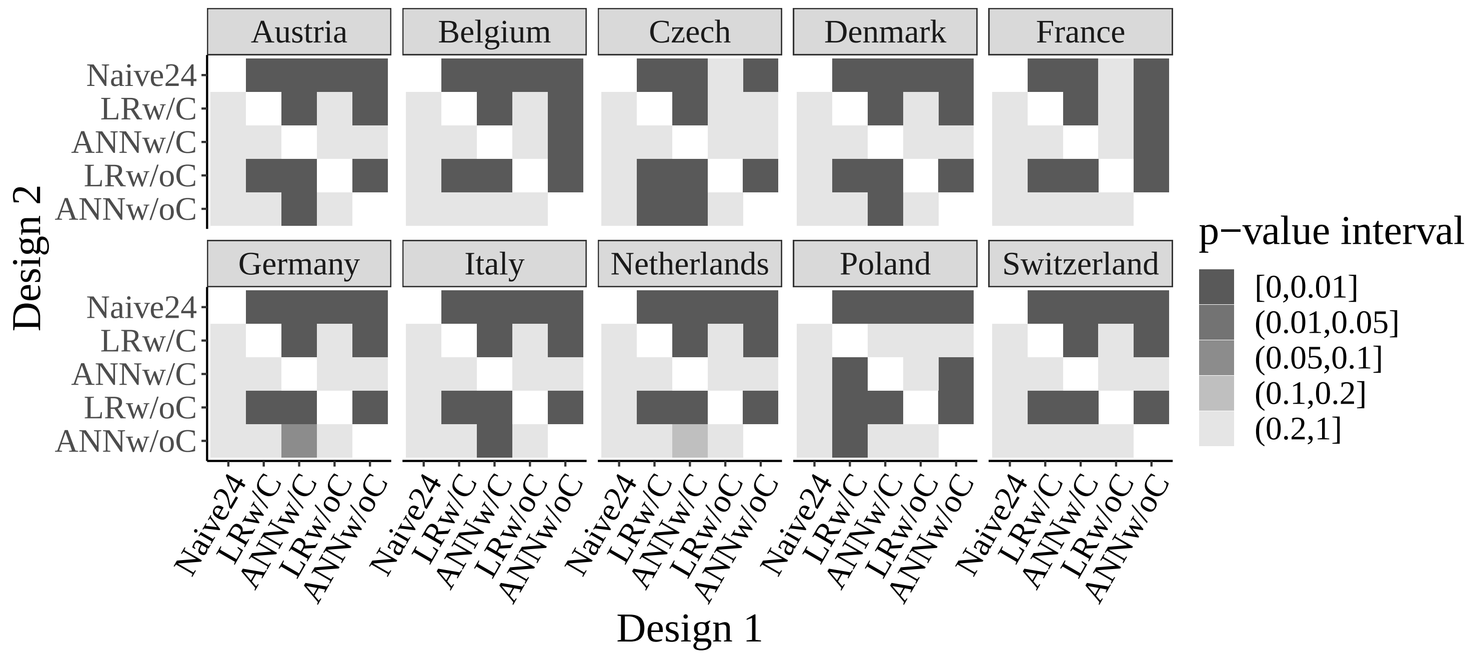


Figure 9: Results of the Diebold-Mariano tests conducted to evaluate the statistical significance of the superiority of one forecasting approach over another. Reading example: *ANNw/C* (Design 1) is superior to *Naive24* (Design 2) in all countries at a significance level $p \leq 0.01$ as depicted by the respective grey tone. In contrast to Fig. 7, this illustration additionally contains the two forecasting approaches without classifier (*ANNw/oC*, *LRw/oC*).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	22.0	24.9	25.7	7.6	22.0	22.0	11.2	35.0	22.5	6.7	0.48	0.60	0.52	0.21	0.48	0.48	0.52	0.60	0.49	0.19
2021	23.5	26.5	26.8	12.8	23.5	23.5	11.6	34.4	23.9	7.5	0.48	0.61	0.51	0.30	0.48	0.48	0.52	0.57	0.49	0.20
2022	24.2	27.7	27.2	19.8	24.2	24.2	11.9	34.4	24.6	11.3	0.47	0.61	0.50	0.41	0.47	0.47	0.53	0.55	0.48	0.26
2023	27.0	30.2	29.1	26.0	27.0	27.0	12.7	34.1	27.2	20.2	0.48	0.62	0.50	0.47	0.48	0.48	0.54	0.53	0.49	0.38
2024	38.2	36.8	39.1	37.8	38.3	38.2	13.3	33.1	36.9	32.1	0.53	0.62	0.54	0.53	0.53	0.54	0.49	0.50	0.52	0.47
2025	47.8	46.4	48.2	47.4	47.8	47.8	13.6	33.4	47.2	43.3	0.59	0.60	0.59	0.58	0.59	0.59	0.46	0.49	0.58	0.54
2026	34.8	35.7	34.7	34.3	34.9	34.6	15.0	32.7	34.9	31.6	0.47	0.50	0.46	0.46	0.47	0.47	0.49	0.47	0.47	0.41
2027	29.9	31.7	29.6	28.9	30.0	29.9	14.9	32.9	30.1	28.2	0.44	0.49	0.44	0.42	0.44	0.44	0.59	0.46	0.45	0.39
2028	30.3	32.0	29.9	28.9	30.4	30.3	17.1	32.2	30.4	29.1	0.44	0.49	0.43	0.41	0.44	0.44	0.60	0.44	0.44	0.38
2029	30.6	32.4	30.5	28.8	31.0	31.0	19.3	32.4	30.9	29.7	0.42	0.48	0.42	0.39	0.43	0.43	0.60	0.43	0.43	0.37
2030	31.3	32.5	30.9	29.0	31.7	31.6	25.2	31.9	31.7	30.6	0.42	0.46	0.41	0.38	0.43	0.43	0.56	0.42	0.43	0.37
2031	32.3	33.3	32.1	29.8	32.6	32.6	32.4	31.8	32.7	31.5	0.40	0.43	0.40	0.36	0.41	0.41	0.50	0.41	0.41	0.35
2032	33.9	34.2	33.6	31.4	34.2	34.2	34.4	31.4	34.4	30.7	0.39	0.40	0.39	0.35	0.40	0.40	0.47	0.39	0.40	0.33
2033	33.2	33.4	33.1	30.6	33.5	33.5	33.7	30.4	33.7	32.1	0.38	0.39	0.38	0.34	0.39	0.39	0.43	0.37	0.39	0.34
2034	34.3	33.7	34.4	31.9	34.5	34.5	33.8	29.5	34.6	30.8	0.37	0.36	0.37	0.33	0.37	0.37	0.38	0.34	0.37	0.31
2035	36.3	37.1	36.4	33.8	36.6	36.6	36.3	28.2	36.6	32.4	0.37	0.37	0.37	0.33	0.37	0.37	0.38	0.31	0.37	0.31
2036	37.5	38.2	37.5	34.3	37.7	37.7	36.5	26.6	37.6	34.6	0.36	0.37	0.36	0.32	0.36	0.36	0.36	0.29	0.36	0.32
2037	39.9	41.1	39.9	35.6	40.2	40.2	35.7	26.2	40.2	36.6	0.37	0.38	0.37	0.32	0.37	0.37	0.34	0.29	0.37	0.33
2038	47.9	47.7	47.8	43.0	48.2	48.2	35.9	27.2	48.4	46.5	0.41	0.41	0.40	0.35	0.41	0.41	0.33	0.29	0.41	0.38
2039	36.8	38.3	36.6	31.4	37.1	37.1	34.8	27.5	37.4	33.2	0.35	0.36	0.35	0.28	0.35	0.35	0.34	0.30	0.36	0.30
2040	43.7	45.2	43.5	37.8	44.2	44.1	37.0	28.3	44.5	39.1	0.39	0.40	0.39	0.32	0.39	0.39	0.35	0.31	0.40	0.34
2041	44.9	46.0	44.4	38.2	45.5	45.5	38.2	30.3	45.9	37.9	0.39	0.40	0.39	0.32	0.40	0.40	0.35	0.32	0.40	0.32
2042	53.5	53.8	52.7	46.1	54.1	54.1	40.1	31.7	54.8	45.9	0.44	0.44	0.43	0.36	0.45	0.45	0.36	0.33	0.45	0.37
2043	56.5	57.3	55.6	48.1	57.2	57.2	43.1	35.6	58.1	54.9	0.45	0.45	0.44	0.36	0.46	0.46	0.37	0.34	0.46	0.41
2044	49.4	51.3	48.4	37.2	49.9	49.9	44.9	37.2	51.0	42.9	0.43	0.43	0.42	0.30	0.44	0.44	0.40	0.36	0.44	0.34
2045	53.9	55.6	52.5	41.8	54.5	54.4	45.8	37.4	55.2	47.7	0.45	0.45	0.44	0.32	0.45	0.45	0.40	0.36	0.45	0.36
2046	56.2	57.9	54.8	45.6	56.5	56.4	48.6	41.4	57.2	46.4	0.46	0.46	0.45	0.33	0.46	0.46	0.42	0.39	0.46	0.37
2047	57.3	59.4	55.9	41.3	57.3	57.3	50.7	45.5	58.3	48.1	0.49	0.49	0.48	0.32	0.49	0.49	0.46	0.43	0.49	0.38
2048	61.1	63.9	59.0	41.1	61.8	61.7	56.4	43.0	63.2	49.6	0.49	0.49	0.48	0.32	0.49	0.49	0.48	0.41	0.50	0.39
2049	58.3	62.1	56.2	40.0	59.3	59.3	54.0	44.0	61.0	50.4	0.49	0.50	0.48	0.32	0.50	0.50	0.49	0.43	0.50	0.40
2050	62.1	65.1	60.9	42.9	63.0	63.0	59.2	48.6	64.8	50.5	0.50	0.51	0.50	0.33	0.51	0.51	0.51	0.45	0.52	0.40
Mean	40.9	42.3	40.9	34.3	41.2	41.2	32.2	33.8	41.6	35.2	0.44	0.47	0.44	0.36	0.44	0.44	0.45	0.41	0.44	0.36

Table 9: Error metrics of the persistence forecast (*Naive24*) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table 4).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.3	7.1	2.5	5.1	5.1	7.8	12.5	5.4	3.0	0.13	0.21	0.17	0.07	0.13	0.13	0.40	0.25	0.14	0.09
2021	4.0	7.1	5.9	3.5	4.0	4.0	7.7	8.9	4.4	4.0	0.10	0.20	0.14	0.09	0.10	0.10	0.39	0.19	0.11	0.11
2022	4.0	7.5	6.6	3.9	4.0	4.0	8.1	11.0	4.3	3.2	0.09	0.20	0.14	0.09	0.09	0.09	0.41	0.21	0.10	0.08
2023	6.2	9.6	7.8	6.1	6.2	6.2	9.2	10.3	6.2	6.7	0.13	0.23	0.16	0.13	0.13	0.13	0.44	0.19	0.13	0.14
2024	12.8	12.6	13.4	11.1	12.8	12.8	9.9	9.6	11.1	10.8	0.19	0.24	0.20	0.17	0.19	0.19	0.40	0.17	0.17	0.17
2025	9.8	14.1	10.6	10.6	8.5	9.5	10.1	8.0	10.2	10.4	0.14	0.21	0.15	0.15	0.12	0.13	0.39	0.14	0.14	0.14
2026	7.6	9.4	8.2	7.4	7.7	7.7	10.8	8.0	7.4	8.5	0.12	0.15	0.13	0.11	0.12	0.12	0.40	0.14	0.12	0.13
2027	8.5	10.4	8.7	8.0	8.6	8.5	11.5	8.6	8.1	9.8	0.14	0.18	0.14	0.13	0.14	0.14	0.51	0.14	0.14	0.15
2028	8.7	10.9	8.9	7.7	8.9	8.9	12.6	7.7	8.5	8.9	0.14	0.19	0.14	0.12	0.15	0.15	0.50	0.12	0.14	0.13
2029	10.2	12.4	10.6	9.0	10.4	10.4	13.5	8.3	10.0	9.4	0.16	0.20	0.16	0.13	0.16	0.16	0.46	0.13	0.16	0.13
2030	11.7	13.6	11.8	10.2	12.0	11.9	16.5	8.8	11.7	10.5	0.17	0.21	0.17	0.15	0.18	0.18	0.39	0.13	0.17	0.14
2031	12.1	13.7	12.2	10.6	12.3	12.3	18.0	8.9	12.3	12.3	0.16	0.19	0.17	0.14	0.17	0.17	0.30	0.13	0.17	0.15
2032	12.4	13.6	12.4	10.9	12.8	12.4	15.8	9.0	13.0	10.9	0.15	0.17	0.15	0.13	0.16	0.15	0.23	0.13	0.16	0.13
2033	12.7	13.5	12.9	11.4	12.8	12.8	16.2	9.2	13.1	12.2	0.15	0.16	0.15	0.13	0.15	0.15	0.21	0.12	0.16	0.14
2034	13.6	13.9	13.7	12.4	13.7	13.6	16.3	9.1	13.8	12.5	0.15	0.16	0.16	0.14	0.16	0.15	0.20	0.12	0.16	0.14
2035	14.8	15.5	14.5	13.5	13.8	14.0	15.2	8.5	14.0	12.6	0.16	0.16	0.15	0.14	0.14	0.15	0.16	0.10	0.15	0.13
2036	14.0	14.5	14.2	12.5	13.9	13.9	14.8	9.2	14.1	12.9	0.14	0.15	0.14	0.12	0.14	0.14	0.15	0.11	0.14	0.13
2037	14.0	14.3	14.0	12.6	13.7	13.7	14.3	10.4	13.9	12.9	0.13	0.14	0.13	0.12	0.13	0.13	0.15	0.12	0.13	0.12
2038	16.0	15.4	15.8	13.8	15.0	15.4	15.3	12.9	16.3	15.1	0.14	0.14	0.14	0.12	0.13	0.14	0.15	0.15	0.15	0.13
2039	14.4	15.0	15.1	12.8	14.9	15.3	14.7	12.7	14.3	12.6	0.14	0.15	0.15	0.12	0.15	0.15	0.15	0.15	0.14	0.12
2040	14.9	15.2	14.9	13.9	14.4	14.5	15.2	12.8	14.9	12.9	0.14	0.14	0.14	0.13	0.14	0.14	0.15	0.15	0.14	0.12
2041	14.5	15.1	14.4	13.6	13.9	14.0	15.2	11.5	14.4	13.0	0.14	0.14	0.14	0.12	0.13	0.13	0.15	0.13	0.14	0.12
2042	17.9	17.6	16.7	14.7	16.4	17.7	15.9	12.4	18.5	16.9	0.16	0.15	0.15	0.12	0.14	0.16	0.15	0.14	0.16	0.14
2043	15.1	16.1	15.5	14.9	14.2	14.2	16.3	14.1	15.0	16.4	0.13	0.14	0.14	0.12	0.13	0.13	0.15	0.15	0.13	0.13
2044	15.1	16.4	15.5	15.4	14.3	14.4	16.0	14.9	15.3	15.7	0.14	0.15	0.15	0.14	0.14	0.14	0.16	0.16	0.14	0.14
2045	15.9	17.5	17.0	17.3	15.2	15.3	17.3	16.6	15.9	16.6	0.14	0.15	0.15	0.14	0.14	0.14	0.16	0.17	0.14	0.14
2046	19.1	19.0	19.1	20.2	15.9	15.6	17.7	18.2	18.5	14.5	0.17	0.17	0.17	0.16	0.14	0.14	0.17	0.18	0.16	0.13
2047	15.1	16.6	16.2	15.5	13.9	14.1	16.9	17.8	14.9	13.9	0.14	0.15	0.15	0.13	0.13	0.13	0.17	0.18	0.14	0.13
2048	22.2	23.7	23.6	16.6	21.5	21.1	18.4	19.6	21.5	14.2	0.20	0.20	0.21	0.14	0.19	0.19	0.18	0.20	0.19	0.13
2049	14.4	16.5	15.6	15.7	13.6	13.8	15.9	18.3	15.0	14.0	0.13	0.15	0.15	0.14	0.12	0.13	0.16	0.19	0.13	0.13
2050	14.9	17.7	17.6	17.2	13.9	14.2	14.9	19.2	15.7	15.1	0.13	0.16	0.16	0.15	0.13	0.13	0.15	0.20	0.14	0.14
Mean	12.6	14.1	13.2	11.8	12.2	12.3	14.1	11.8	12.6	11.7	0.14	0.17	0.15	0.13	0.14	0.14	0.26	0.15	0.14	0.13

Table 10: Error metrics of the approach using multiple linear regression with a multinominal logistic regression classifier (*LRw/C*) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table 5).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.8	7.2	3.8	5.2	5.0	3.3	10.2	5.7	6.0	0.13	0.22	0.17	0.11	0.13	0.13	0.17	0.21	0.14	0.17
2021	5.5	6.2	7.2	4.9	5.3	5.2	2.7	10.0	5.7	5.6	0.13	0.17	0.16	0.13	0.13	0.12	0.14	0.20	0.14	0.15
2022	5.7	6.1	7.8	6.2	6.0	5.9	3.4	11.9	6.0	7.0	0.13	0.16	0.17	0.14	0.14	0.14	0.17	0.22	0.14	0.17
2023	8.6	8.3	10.2	8.7	8.5	8.6	3.6	11.9	8.6	8.7	0.17	0.19	0.20	0.17	0.17	0.17	0.17	0.22	0.17	0.18
2024	14.0	9.3	15.0	12.6	13.9	14.1	3.2	10.1	13.2	13.6	0.21	0.17	0.22	0.19	0.21	0.21	0.13	0.18	0.20	0.21
2025	8.1	12.1	8.8	8.7	7.7	8.1	3.4	9.3	7.8	7.8	0.11	0.18	0.12	0.12	0.11	0.11	0.14	0.16	0.11	0.11
2026	7.9	8.5	9.0	8.4	9.1	7.9	3.3	9.7	8.1	9.6	0.12	0.14	0.14	0.13	0.14	0.12	0.12	0.16	0.13	0.14
2027	9.6	9.6	11.2	9.7	9.8	9.7	4.0	13.2	9.3	10.9	0.16	0.17	0.18	0.16	0.16	0.16	0.18	0.20	0.15	0.16
2028	10.8	18.8	9.6	18.3	11.3	9.2	4.6	14.8	11.0	14.7	0.18	0.34	0.16	0.30	0.19	0.16	0.19	0.24	0.19	0.22
2029	9.6	9.0	10.9	9.4	9.6	9.0	5.9	11.1	8.9	13.4	0.14	0.14	0.16	0.14	0.14	0.14	0.20	0.16	0.14	0.18
2030	7.6	7.2	8.5	7.1	7.3	6.5	14.0	8.4	6.5	12.3	0.11	0.11	0.13	0.10	0.11	0.10	0.33	0.13	0.10	0.16
2031	6.7	7.0	7.1	6.7	6.4	6.3	16.1	7.0	6.2	9.7	0.09	0.10	0.10	0.09	0.09	0.09	0.27	0.10	0.09	0.12
2032	6.0	7.1	6.2	6.0	5.8	5.6	8.0	8.2	5.8	8.1	0.08	0.09	0.08	0.07	0.07	0.07	0.12	0.12	0.07	0.10
2033	8.2	7.9	8.5	8.7	7.1	7.4	11.3	9.5	7.0	13.2	0.10	0.10	0.10	0.10	0.09	0.09	0.15	0.13	0.08	0.14
2034	8.3	7.9	9.6	8.2	8.2	7.7	11.8	6.1	8.3	14.2	0.10	0.09	0.11	0.10	0.10	0.09	0.15	0.08	0.10	0.15
2035	9.7	10.1	9.9	10.7	9.5	9.7	11.1	6.7	9.3	12.2	0.10	0.11	0.11	0.11	0.10	0.10	0.12	0.08	0.10	0.13
2036	8.2	8.3	8.0	9.4	7.6	8.0	10.1	6.1	9.0	8.0	0.08	0.09	0.08	0.09	0.08	0.08	0.11	0.07	0.09	0.08
2037	7.8	8.0	7.3	9.0	7.3	8.1	9.1	6.3	7.4	9.8	0.08	0.08	0.07	0.08	0.07	0.08	0.10	0.08	0.07	0.09
2038	7.7	7.3	6.9	8.1	5.8	7.2	8.1	5.6	7.3	9.0	0.07	0.07	0.06	0.07	0.05	0.07	0.08	0.07	0.07	0.08
2039	6.6	9.5	7.2	5.7	6.5	7.6	7.4	5.6	5.4	8.3	0.07	0.10	0.07	0.06	0.07	0.08	0.08	0.07	0.06	0.08
2040	4.9	5.4	5.0	5.4	4.5	5.1	6.1	5.2	4.9	5.7	0.05	0.05	0.05	0.05	0.04	0.05	0.06	0.06	0.05	0.05
2041	13.9	13.3	15.3	16.7	12.8	15.9	18.5	10.6	13.1	9.7	0.13	0.13	0.15	0.15	0.12	0.15	0.18	0.12	0.12	0.09
2042	15.0	15.3	14.1	14.7	14.0	13.7	17.1	12.2	15.3	13.3	0.13	0.13	0.13	0.12	0.12	0.12	0.17	0.14	0.14	0.11
2043	24.4	28.6	23.9	27.8	24.4	23.8	31.7	19.7	28.3	26.8	0.21	0.25	0.21	0.22	0.21	0.21	0.29	0.20	0.24	0.22
2044	11.2	11.9	17.5	15.2	9.6	9.4	12.4	9.2	12.7	13.4	0.11	0.11	0.17	0.13	0.09	0.09	0.12	0.10	0.12	0.12
2045	12.3	13.5	13.9	14.7	10.4	11.0	14.9	12.9	11.4	14.9	0.11	0.12	0.13	0.12	0.09	0.10	0.14	0.13	0.10	0.12
2046	15.2	18.7	16.0	17.2	13.3	18.8	15.5	13.2	21.6	33.2	0.14	0.17	0.15	0.14	0.12	0.17	0.15	0.14	0.20	0.29
2047	9.7	10.7	10.3	10.9	8.2	8.5	11.8	11.8	9.5	16.3	0.09	0.10	0.10	0.09	0.08	0.08	0.12	0.12	0.09	0.15
2048	23.4	26.4	23.6	14.8	21.5	24.5	32.1	20.1	23.3	56.4	0.21	0.23	0.21	0.13	0.19	0.21	0.30	0.20	0.20	0.49
2049	11.8	18.4	11.3	16.9	11.0	10.8	14.3	12.9	11.1	15.9	0.11	0.17	0.11	0.15	0.10	0.10	0.15	0.13	0.10	0.14
2050	10.1	13.1	11.5	10.1	8.9	10.3	12.8	14.1	12.2	26.5	0.09	0.12	0.11	0.09	0.08	0.09	0.13	0.15	0.11	0.23
Mean	10.1	11.3	10.9	10.8	9.6	10.0	10.7	10.4	10.3	14.0	0.12	0.14	0.13	0.12	0.12	0.12	0.16	0.14	0.12	0.16

Table 11: Error metrics of the approach using a feedforward neural network with a feedforward neural network classifier (*ANNw/C*) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table 6).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.3	7.1	2.5	5.1	5.1	7.8	12.5	5.4	3.0	0.13	0.21	0.17	0.07	0.13	0.13	0.40	0.25	0.14	0.09
2021	4.0	7.1	5.9	3.5	4.0	4.0	7.7	8.9	4.4	4.0	0.10	0.20	0.14	0.09	0.10	0.10	0.39	0.19	0.11	0.11
2022	4.0	7.5	6.6	3.9	4.0	4.0	8.1	11.0	4.3	3.2	0.09	0.20	0.14	0.09	0.09	0.09	0.41	0.21	0.10	0.08
2023	6.2	9.6	7.8	6.1	6.2	6.2	9.2	10.3	6.2	6.7	0.13	0.23	0.16	0.13	0.13	0.13	0.44	0.19	0.13	0.14
2024	32.6	23.9	31.4	29.0	32.5	32.5	12.2	8.7	30.9	30.1	0.47	0.44	0.46	0.43	0.47	0.47	0.50	0.15	0.46	0.43
2025	52.2	45.6	52.1	51.1	52.2	52.2	14.0	8.4	49.3	52.7	0.70	0.64	0.69	0.68	0.70	0.70	0.56	0.14	0.66	0.68
2026	32.1	30.3	32.0	32.0	31.8	31.8	15.2	8.3	31.3	32.8	0.48	0.48	0.48	0.48	0.48	0.48	0.58	0.14	0.47	0.46
2027	10.1	11.8	10.2	9.6	10.0	10.0	13.1	8.4	9.9	11.5	0.17	0.21	0.17	0.16	0.17	0.17	0.58	0.14	0.17	0.18
2028	9.5	11.5	9.5	8.4	9.7	9.6	12.7	8.5	9.3	10.0	0.15	0.20	0.15	0.13	0.16	0.16	0.51	0.13	0.15	0.15
2029	11.0	12.9	11.3	9.5	11.3	11.2	13.1	8.7	11.0	10.3	0.17	0.21	0.17	0.14	0.18	0.17	0.45	0.13	0.17	0.15
2030	12.5	14.0	12.6	10.8	12.8	12.7	15.6	9.5	12.6	11.4	0.18	0.22	0.18	0.15	0.19	0.19	0.38	0.14	0.19	0.15
2031	15.8	16.2	15.0	14.3	15.9	15.8	18.0	9.4	15.7	15.8	0.22	0.23	0.21	0.19	0.22	0.22	0.31	0.14	0.22	0.19
2032	27.2	27.1	25.4	26.6	27.2	27.0	24.2	10.4	27.2	19.1	0.33	0.34	0.31	0.32	0.33	0.33	0.35	0.15	0.33	0.22
2033	31.9	31.8	30.1	31.2	31.7	31.5	29.7	14.9	31.8	26.5	0.37	0.37	0.36	0.36	0.37	0.37	0.39	0.19	0.37	0.29
2034	35.4	34.0	34.9	31.9	35.5	35.3	34.1	17.1	35.4	28.4	0.39	0.39	0.39	0.35	0.40	0.39	0.40	0.21	0.39	0.30
2035	48.1	47.9	47.9	46.5	48.9	48.8	46.8	26.4	48.9	40.5	0.49	0.49	0.48	0.46	0.49	0.49	0.49	0.30	0.49	0.39
2036	51.8	50.9	51.4	51.5	52.5	52.3	49.9	25.4	52.4	45.1	0.51	0.50	0.51	0.49	0.52	0.51	0.50	0.29	0.51	0.42
2037	62.0	58.4	61.5	62.1	62.1	62.0	52.7	26.7	62.0	54.1	0.58	0.55	0.57	0.55	0.58	0.58	0.52	0.29	0.58	0.48
2038	73.3	69.2	72.6	75.3	73.2	73.2	54.0	15.1	73.3	72.2	0.64	0.61	0.64	0.62	0.64	0.64	0.52	0.18	0.64	0.59
2039	58.2	55.8	56.7	58.2	58.0	57.8	45.5	16.1	58.2	54.9	0.56	0.53	0.54	0.52	0.56	0.55	0.45	0.18	0.55	0.49
2040	57.9	57.4	54.7	57.1	57.8	57.6	46.0	16.9	58.0	45.5	0.53	0.52	0.51	0.49	0.53	0.53	0.45	0.19	0.53	0.40
2041	55.8	56.2	51.5	55.4	55.1	55.0	43.9	17.4	55.5	43.1	0.52	0.52	0.48	0.47	0.51	0.51	0.43	0.20	0.51	0.38
2042	64.8	64.3	60.0	66.2	64.5	64.4	48.2	20.3	64.9	49.1	0.55	0.54	0.52	0.51	0.55	0.55	0.45	0.22	0.55	0.40
2043	70.9	70.3	69.0	73.6	71.2	71.0	54.5	31.7	71.6	66.2	0.60	0.59	0.59	0.56	0.61	0.61	0.50	0.31	0.60	0.51
2044	51.7	51.7	49.3	43.9	50.6	50.6	42.3	28.4	51.7	36.4	0.48	0.47	0.46	0.37	0.47	0.47	0.40	0.29	0.48	0.32
2045	53.9	55.3	50.7	48.6	53.5	53.4	46.2	32.6	54.2	40.1	0.46	0.47	0.44	0.38	0.46	0.46	0.42	0.31	0.46	0.31
2046	61.7	63.1	60.0	59.4	62.0	61.9	55.3	40.2	62.8	22.1	0.54	0.54	0.54	0.46	0.55	0.55	0.52	0.39	0.55	0.20
2047	46.1	47.2	43.3	37.5	45.4	45.3	41.0	34.8	46.3	16.3	0.42	0.42	0.40	0.30	0.42	0.42	0.40	0.34	0.42	0.15
2048	68.1	71.1	65.4	26.3	68.8	68.6	61.2	45.6	70.6	17.9	0.59	0.60	0.58	0.22	0.60	0.60	0.58	0.45	0.60	0.16
2049	56.9	58.4	50.3	16.2	56.4	56.5	47.4	37.6	57.8	18.8	0.51	0.51	0.47	0.14	0.51	0.51	0.47	0.38	0.51	0.17
2050	48.4	52.1	48.2	16.2	50.1	49.6	45.7	37.4	50.7	20.1	0.43	0.45	0.44	0.14	0.44	0.44	0.45	0.37	0.44	0.18
Mean	39.3	39.3	38.2	34.3	39.3	39.3	32.7	19.6	39.5	29.3	0.40	0.42	0.40	0.34	0.41	0.40	0.46	0.23	0.40	0.30

Table 12: Error metrics of the approach using multiple linear regression without classifier (*LRw/oC*) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table 7).

Year	Mean absolute error (MAE) [EUR/MWh]										Mean absolute percentage error (MAPE) [–]									
	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL	AT	BE	CH	CZ	DE	DK	FR	IT	NL	PL
2020	5.1	7.8	7.2	3.8	5.2	5.0	3.3	10.2	5.7	6.0	0.13	0.22	0.17	0.11	0.13	0.13	0.17	0.21	0.14	0.17
2021	5.5	6.2	7.2	4.9	5.3	5.2	2.7	10.0	5.7	5.6	0.13	0.17	0.16	0.13	0.13	0.12	0.14	0.20	0.14	0.15
2022	5.7	6.1	7.8	6.2	6.0	5.9	3.4	11.9	6.0	7.0	0.13	0.16	0.17	0.14	0.14	0.14	0.17	0.22	0.14	0.17
2023	8.6	8.3	10.2	8.7	8.5	8.6	3.6	11.9	8.6	8.7	0.17	0.19	0.20	0.17	0.17	0.17	0.17	0.22	0.17	0.18
2024	13.6	12.2	16.0	17.0	13.7	14.6	7.2	10.5	12.9	14.4	0.20	0.22	0.24	0.26	0.21	0.22	0.28	0.19	0.20	0.22
2025	7.6	10.0	9.8	7.6	7.7	8.3	5.0	8.5	7.1	10.2	0.11	0.15	0.14	0.11	0.11	0.12	0.20	0.15	0.10	0.14
2026	8.6	8.2	10.5	10.2	8.8	9.4	5.1	11.0	8.6	10.9	0.13	0.13	0.16	0.15	0.13	0.14	0.19	0.18	0.13	0.16
2027	6.4	6.7	7.6	7.2	6.1	7.3	3.2	9.8	6.0	7.6	0.11	0.12	0.13	0.12	0.10	0.12	0.15	0.16	0.10	0.12
2028	6.6	7.2	7.3	7.1	6.6	6.8	4.3	9.2	6.7	7.0	0.11	0.13	0.12	0.11	0.11	0.11	0.17	0.15	0.11	0.11
2029	6.7	7.7	8.0	7.5	6.6	6.3	6.4	8.4	6.4	6.9	0.11	0.13	0.12	0.12	0.10	0.10	0.22	0.13	0.10	0.10
2030	7.5	8.6	8.9	10.4	7.1	7.1	13.9	9.8	6.9	9.3	0.11	0.14	0.13	0.15	0.11	0.11	0.33	0.15	0.10	0.12
2031	6.7	9.3	8.9	13.9	7.5	7.6	14.8	9.0	7.4	12.3	0.09	0.14	0.12	0.19	0.11	0.11	0.25	0.13	0.11	0.15
2032	8.4	10.0	10.1	29.8	10.7	10.7	10.5	7.5	8.3	12.7	0.10	0.13	0.13	0.36	0.13	0.13	0.15	0.11	0.10	0.15
2033	8.5	8.5	9.4	32.6	10.3	10.4	10.4	5.8	8.3	10.6	0.10	0.10	0.12	0.39	0.13	0.13	0.14	0.08	0.10	0.12
2034	8.6	7.6	9.1	34.2	8.3	10.3	10.1	7.6	8.0	9.7	0.10	0.09	0.11	0.40	0.10	0.12	0.13	0.10	0.09	0.11
2035	9.8	9.6	10.3	49.6	8.2	10.1	8.5	5.2	8.9	11.1	0.11	0.10	0.11	0.52	0.09	0.11	0.10	0.06	0.10	0.12
2036	9.5	8.4	9.8	59.2	8.1	12.6	7.9	5.3	8.3	11.9	0.10	0.09	0.10	0.59	0.08	0.13	0.09	0.06	0.09	0.12
2037	11.5	10.5	10.7	78.3	10.9	12.2	6.8	6.9	10.0	15.1	0.11	0.10	0.11	0.73	0.11	0.12	0.07	0.08	0.10	0.14
2038	14.1	9.3	13.0	84.3	10.2	13.5	7.6	6.2	14.7	15.0	0.13	0.09	0.12	0.73	0.09	0.12	0.08	0.07	0.13	0.13
2039	14.3	12.2	14.8	62.5	13.9	15.5	8.7	6.3	16.3	16.6	0.15	0.12	0.15	0.58	0.14	0.16	0.09	0.08	0.17	0.16
2040	11.3	9.4	11.0	64.8	9.4	16.1	6.1	5.2	11.5	13.2	0.11	0.09	0.11	0.58	0.09	0.16	0.06	0.06	0.11	0.13
2041	14.8	14.1	14.3	70.7	13.0	15.7	10.8	9.7	14.8	14.6	0.14	0.13	0.14	0.62	0.13	0.15	0.11	0.11	0.14	0.14
2042	16.0	12.9	14.7	71.0	13.8	15.8	11.1	12.0	16.0	16.0	0.14	0.12	0.13	0.57	0.13	0.14	0.11	0.13	0.14	0.14
2043	17.7	13.5	16.2	59.8	16.3	18.0	13.1	18.2	19.5	21.1	0.16	0.12	0.15	0.47	0.15	0.16	0.13	0.19	0.17	0.18
2044	16.5	13.6	10.9	23.6	12.6	18.4	10.6	14.6	16.8	17.6	0.16	0.13	0.10	0.21	0.12	0.18	0.11	0.16	0.16	0.16
2045	17.6	14.5	12.5	24.6	13.4	18.0	12.7	16.3	17.8	20.7	0.16	0.13	0.11	0.20	0.12	0.16	0.12	0.17	0.16	0.17
2046	19.8	16.7	14.5	27.9	16.2	24.8	15.1	18.7	19.5	20.9	0.18	0.15	0.13	0.22	0.15	0.23	0.15	0.19	0.17	0.18
2047	17.1	13.6	13.4	19.2	12.8	15.9	12.5	17.0	16.0	18.2	0.16	0.13	0.13	0.16	0.12	0.15	0.13	0.18	0.15	0.16
2048	22.4	20.2	21.7	28.1	18.1	28.3	21.3	19.6	20.8	21.6	0.20	0.17	0.19	0.23	0.16	0.25	0.20	0.19	0.18	0.19
2049	22.0	16.5	15.6	16.0	14.4	18.7	16.4	17.9	18.9	20.0	0.20	0.15	0.15	0.14	0.13	0.17	0.17	0.19	0.17	0.18
2050	22.3	17.6	16.2	17.5	14.6	16.8	16.2	20.3	19.6	21.3	0.20	0.15	0.15	0.15	0.13	0.15	0.16	0.21	0.17	0.19
Mean	12.0	10.9	11.5	30.9	10.5	12.7	9.3	11.0	11.7	13.4	0.14	0.14	0.14	0.31	0.12	0.15	0.15	0.15	0.13	0.15

Table 13: Error metrics of the approach using a feedforward neural network without classifier (*ANNw/oC*) with the 0.25% worst forecasts per country being filtered. Although only very few data points have been removed, the metrics substantially improve as compared to the full data set (cf. Table 8).

Conejo, A.J., Contreras, J., Espínola, R., Plazas, M.A., 2005. Forecasting electricity prices for a day-ahead pool-based electric energy market. International Journal of Forecasting 21, 435–462. doi:10.1016/j.ijforecast.2004.12.005.

Diebold, F.X., Mariano, R.S., 1995. Comparing Predictive Accuracy. Journal of Business & Economic Statistics 13, 253–263. doi:10.1080/07350015.1995.10524599.

Ding, Y., 2018. A novel decompose-ensemble methodology with AIC-ANN approach for crude oil forecasting. Energy 154, 328–336. doi:10.1016/j.energy.2018.04.133.

Dudek, G., 2016. Multilayer perceptron for GEFCom2014 probabilistic electricity price forecasting. International Journal of Forecasting 32, 1057–1060. doi:10.1016/j.ijforecast.2015.11.009.

ENTSO-E, 2016. Ten Year Network Development Plan 2016: Market Modeling Data. URL: https://www.entsoe.eu/Documents/TYNDP%20documents/TYNDP%202016/rgips/TYNDP2016%20market%20modelling%20data.xlsx.

ENTSO-E, 2017. Transparency Platform. URL: https://transparency.entsoe.eu/.

Esmaeili Aliabadi, D., Kaya, M., Sahin, G., 2017. Competition, risk and learning in electricity markets: An agent-based simulation study. Applied Energy 195, 1000–1011. doi:10.1016/j.apenergy.2017.03.121.

Fan, X., Li, S., Tian, L., 2015. Chaotic characteristic identification for carbon price and an multi-layer perceptron network prediction model. Expert Systems with Applications 42, 3945–3952. doi:10.1016/j.eswa.2014.12.047.

Fraunholz, C., Hladik, D., Keles, D., Möst, D., Fichtner, W., 2020. On the Long-Term Efficiency of Market Splitting in Germany. doi:10.5445/IR/1000105902.

Fraunholz, C., Keles, D., Fichtner, W., 2019a. Agent-Based Generation and Storage Expansion Planning in Interconnected Electricity Markets, in: 2019 16th International Conference on the European Energy Market (EEM), IEEE, Piscataway, NJ. doi:10.1109/EEM.2019.8916348.

Fraunholz, C., Keles, D., Fichtner, W., 2019b. On the Role of Electricity Storage in Capacity Remuneration Mechanisms. doi:10.5445/IR/1000104471.

Genoese, M., 2010. Energiewirtschaftliche Analysen des deutschen Strommarkts mit agentenbasierter Simulation. Nomos, Baden-Baden, Germany.

Ghoddusi, H., Creamer, G.G., Rafizadeh, N., 2019. Machine learning in energy economics and finance: A review. Energy Economics 81, 709–727. doi:10.1016/j.eneco.2019.05.006.

Giovanelli, C., Sierla, S., Ichise, R., Vyatkin, V., 2018. Exploiting Artificial Neural Networks for the Prediction of Ancillary Energy Market Prices. Energies 11. URL: doi:10.3390/en11071906.

Glorot, X., Bengio, Y., 2010. Understanding the difficulty of training deep feedforward neural networks, in: Teh, Y.W., Titterington, M. (Eds.), Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, PMLR, Chia Laguna Resort, Sardinia, Italy. pp. 249–256. URL: http://proceedings.mlr.press/v9/glorot10a.html.

Guerci, E., Rastegar, M.A., Cincotti, S., 2010. Agent-based Modeling and Simulation of Competitive Wholesale Electricity Markets, in: Rebennack, S., Pardalos, P.M., Pereira, M.V.F., Iliadis, N.A. (Eds.), Handbook of Power Systems II. Springer, Berlin, Heidelberg, Germany. Energy Systems, pp. 241–286. doi:10.1007/978-3-642-12686-4_9.

Hansen, P., Liu, X., Morrison, G.M., 2019. Agent-based modelling and socio-technical energy transitions: A systematic literature review. Energy Research & Social Science 49, 41–52. doi:10.1016/j.erss.2018.10.021.

Huang, L., Wang, J., 2018. Global crude oil price prediction and synchronization based accuracy evaluation using random wavelet neural network. Energy 151, 875–888. doi:10.1016/j.energy.2018.03.099.

Jammazi, R., Aloui, C., 2012. Crude oil price forecasting: Experimental evidence from wavelet decomposition and neural network modeling. Energy Economics 34, 828–841. doi:10.1016/j.eneco.2011.07.018.

Just, S., Weber, C., 2008. Pricing of reserves: Valuing system reserve capacity against spot prices in electricity markets. Energy Economics 30, 3198–3221. doi:10.1016/j.eneco.2008.05.004.

Keles, D., Bublitz, A., Zimmermann, F., Genoese, M., Fichtner, W., 2016a. Analysis of design options for the electricity market: The German case. Applied Energy 183, 884–901. doi:10.1016/j.apenergy.2016.08.189.

Keles, D., Genoese, M., Möst, D., Fichtner, W., 2012. Comparison of extended mean-reversion and time series models for electricity spot price simulation considering negative prices. Energy Economics 34, 1012–1032. doi:10.1016/j.eneco.2011.08.012.

Keles, D., Scelle, J., Paraschiv, F., Fichtner, W., 2016b. Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. Applied Energy 162, 218–230. doi:10.1016/j.apenergy.2015.09.087.

Kingma, D.P., Ba, J., 2017. Adam: A Method for Stochastic Optimization. URL: http://arxiv.org/pdf/1412.6980v9.

Kraft, E., Keles, D., Fichtner, W., 2020. Modeling of frequency containment reserve prices with econometrics and artificial intelligence. Journal of Forecasting (in press). doi:10.1002/for.2693.

Kraft, E., Rominger, J., Mohiuddin, V., Keles, D., 2019. Forecasting of Frequency Containment Reserve Prices Using Econometric and Artificial Intelligence Approaches, in: 11. Internationale Energiewirtschaftstagung (IEWT). URL: https://doi.org/10.5445/IR/1000091736/pub.

Lago, J., de Ridder, F., de Schutter, B., 2018a. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. Applied Energy 221, 386–405. doi:10.1016/j.apenergy.2018.02.069.

Lago, J., de Ridder, F., Vrancx, P., de Schutter, B., 2018b. Forecasting day-ahead electricity prices in Europe: The importance of considering market integration. Applied Energy 211, 890–903. doi:10.1016/j.apenergy.2017.11.098.

Lee, K.Y., Cha, Y.T., Park, J.H., 1992. Short-term load forecasting using an artificial neural network. IEEE Transactions on Power Systems 7, 124–132. doi:10.1109/59.141695.

Leuthold, F.U., Weigt, H., von Hirschhausen, C., 2008. ELMOD – A Model of the European Electricity Market. doi:10.2139/ssrn.1169082.

Liu, X.Q., Ang, B.W., Goh, T.N., 1991. Forecasting of electricity consumption: a comparison between an econometric model and a neural network model, in: 1991 IEEE International Joint Conference on Neural Networks, IEEE. pp. 1254–1259. doi:10.1109/IJCNN.1991.170569.

Louwen, A., Junginger, M., Krishnan, S., 2018. Technological Learning in Energy Modelling: Experience Curves. URL: http://reflex-project.eu/wp-content/uploads/2018/12/REFLEX_policy_brief_Experience_curves_12_2018.pdf.

Mainzer, K., Killinger, S., McKenna, R., Fichtner, W., 2017. Assessment of rooftop photovoltaic potentials at the urban level using publicly available geodata and image recognition techniques. Solar Energy 155, 561–573. doi:10.1016/j.solener.2017.06.065.

Mengelkamp, E., Gärttner, J., Weinhardt, C., 2018. Intelligent Agent Strategies for Residential Customers in Local Electricity Markets, in: Proceedings of the Ninth International Conference on Future Energy Systems, ACM, New York, NY, USA. pp. 97–107. doi:10.1145/3208903.3208907.

Moshiri, S., Foroutan, F., 2006. Forecasting Nonlinear Crude Oil Futures Prices. The Energy Journal 27. doi:10.5547/ISSN0195-6574-EJ-Vol27-No4-4.

NEMO Committee, 2019. EUPHEMIA Public Description: Single Price Coupling Algorithm. URL: https://www.epexspot.com/sites/default/files/2020-02/Euphemia_Public%20Description_Single%20Price%20Coupling%20Algorithm_190410.pdf.

Oksuz, I., Ugurlu, U., 2019. Neural Network Based Model Comparison for Intraday Electricity Price Forecasting. Energies 12, 4557. doi:10.3390/en12234557.

Park, D.C., El-Sharkawi, M.A., Marks, R.J., Atlas, L.E., Damborg, M.J., 1991. Electric load forecasting using an artificial neural network. IEEE Transactions on Power Systems 6, 442–449. doi:10.1109/59.76685.

Peng, L., Liu, S., Liu, R., Wang, L., 2018. Effective long short-term memory with differential evolution algorithm for electricity price prediction. Energy 162, 1301–1314. doi:10.1016/j.energy.2018.05.052.

Petitet, M., 2016. Long-term dynamics of investment decisions in electricity markets with variable renewables development and adequacy objectives. Dissertation. PSL Research University. Paris, France. URL: https://tel.archives-ouvertes.fr/tel-01471847.

Pindoriya, N.M., Singh, S.N., Singh, S.K., 2008. An Adaptive Wavelet Neural Network-Based Energy Price Forecasting in Electricity Markets. IEEE Transactions on Power Systems 23, 1423–1432. doi:10.1109/TPWRS.2008.922251.

Pinto, T., Sousa, T.M., Praça, I., Vale, Z., Morais, H., 2016. Support Vector Machines for decision support in electricity markets' strategic bidding. Neurocomputing 172, 438–445. doi:10.1016/j.neucom.2015.03.102.

Pinto, T., Sousa, T.M., Vale, Z., 2012. Dynamic artificial neural network for electricity market prices forecast, in: IEEE 16th International Conference on Intelligent Engineering Systems (INES), 2012, IEEE, Piscataway, NJ. pp. 311–316. doi:10.1109/INES.2012.6249850.

Prasanna, A., Holzhauer, S., Krebs, F., 2019. Overview of machine learning and data-driven methods in agent-based modeling of energy markets, in: David, K., Geihs, K., Lange, M., Stumme, G. (Eds.), INFORMATIK 2019: 50 Jahre Gesellschaft für Informatik – Informatik für Gesellschaft, Gesellschaft für Informatik e.V, Bonn, Germany. pp. 571–584. doi:10.18420/inf2019_73.

Reeg, M., Hauser, W., Wassermann, S., Kast, T., Klann, U., Nienhaus, K., Pfenning, U., Weimer-Jehle, W., 2012. AMIRIS: An Agent-Based Simulation Model for the Analysis of Different Support Schemes and Their Effects on Actors Involved in the Integration of Renewable Energies into Energy Markets, in: 2012 23rd International Workshop on Database and Expert Systems Applications, IEEE. pp. 339–344. doi:10.1109/DEXA.2012.54.

Ringler, P., Keles, D., Fichtner, W., 2016. Agent-based modelling and simulation of smart electricity grids and markets – A literature review. Renewable and Sustainable Energy Reviews 57, 205–215. doi:10.1016/j.rser.2015.12.169.

Ringler, P., Keles, D., Fichtner, W., 2017. How to benefit from a common European electricity market design. Energy Policy 101, 629–643. doi:10.1016/j.enpol.2016.11.011.

Rodriguez, C.P., Anders, G.J., 2004. Energy Price Forecasting in the Ontario Competitive Power System Market. IEEE Transactions on Power Systems 19, 366–374. doi:10.1109/TPWRS.2003.821470.

Scheidt, M., 2002. Ein Modell zur Mikrosimulation des Spothandels von Strom auf der Basis eines Multi-Agenten-Systems. Dissertation. RWTH Aachen. Aachen, Germany. URL: http://publications.rwth-aachen.de/record/56936.

Schröder, A., Kunz, F., Meiss, J., Mendelevitch, R., von Hirschhausen, C., 2013. Current and Prospective Costs of Electricity Generation until 2050. Deutsches Institut für Wirtschaftsforschung, Berlin, Germany.

Siemens Gamesa, 2019. ETES – Electric Thermal Energy Storage: Strommarkttreffen May 2019. URL: https://www.strommarkttreffen.org/2019-05-10_Schumacher_ETES-Electric_Thermal_Energy_Storage.pdf.

Singh, N., Mohanty, S.R., Dev Shukla, R., 2017. Short term electricity price forecast based on environmentally adapted generalized neuron. Energy 125, 127–139. doi:10.1016/j.energy.2017.02.094.

S&P Global Platts, 2015. World Electric Power Plants Database. URL: http://www.platts.com/products/world-electric-power-plants-database.

Staudt, P., Träris, Y., Rausch, B., Weinhardt, C., 2018. Predicting Redispatch in the German Electricity Market using Information Systems based on Machine Learning, in: 39th International Conference on Information Systems (ICIS 2018).

Sun, G., Chen, T., Wei, Z., Sun, Y., Zang, H., Chen, S., 2016. A Carbon Price Forecasting Model Based on Variational Mode Decomposition and Spiking Neural Networks. Energies 9, 54. doi:10.3390/en9010054.

Swider, D.J., Weber, C., 2007. Extended ARMA models for estimating price developments on day-ahead electricity markets. Electric Power Systems Research 77, 583–593. doi:10.1016/j.epsr.2006.05.013.

Ugurlu, U., Oksuz, I., Tas, O., 2018. Electricity Price Forecasting Using Recurrent Neural Networks. Energies 11, 1255. doi:10.3390/en11051255.

de Vita, A., Tasios, N., Evangelopoulou, S., Forsell, N., Fragiadakis, K., Fragkos, P., Frank, S., Gomez-Sanabria, A., Gusti, M., Capros, P., Havlík, P., Höglund-Isaksson, L., Kannavou, M., Karkatsoulis, P., Kesting, M., Kouvaritakis, N., Nakos, C., Obersteiner, M., Papadopoulos, D., Paroussos, L., Petropoulos, A., Purohit, P., Siskos, P., Tsani, S., Winiwarter, W., Witzke, H.P., Zampara, M., 2016. EU reference scenario 2016: Energy, transport and GHG emissions: trends to 2050. Publications Office, Luxembourg.

Wang, D., Luo, H., Grunder, O., Lin, Y., Guo, H., 2017. Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm. Applied Energy 190, 390–407. doi:10.1016/j.apenergy.2016.12.134.

Wehinger, L.A., Hug-Glanzmann, G., Galus, M.D., Andersson, G., 2013. Modeling electricity wholesale markets with model predictive and profit maximizing agents.

IEEE Transactions on Power Systems 28, 868–876. doi:10.1109/TPWRS.2012.2213277.

Weidlich, A., Veit, D., 2008. A critical survey of agent-based wholesale electricity market models. Energy Economics 30, 1728–1759. doi:10.1016/j.eneco.2008.01.003.

Weron, R., 2014. Electricity price forecasting: A review of the state-of-the-art with a look into the future. International Journal of Forecasting 30, 1030–1081. doi:10.1016/j.ijforecast.2014.08.008.

Yadav, A.K., Chandel, S.S., 2014. Solar radiation prediction using Artificial Neural Network techniques: A review. Renewable and Sustainable Energy Reviews 33, 772–781. doi:10.1016/j.rser.2013.08.055.

Yu, L., Zhao, Y., Tang, L., 2017. Ensemble Forecasting for Complex Time Series Using Sparse Representation and Neural Networks. Journal of Forecasting 36, 122–138. doi:10.1002/for.2418.

Zhao, Y., Li, J., Yu, L., 2017. A deep learning ensemble approach for crude oil price forecasting. Energy Economics 66, 9–16. doi:10.1016/j.eneco.2017.05.023.

Zhou, Z., Chan, W.K., Chow, J.H., 2007. Agent-based simulation of electricity markets: a survey of tools. Artificial Intelligence Review 28, 305–342. doi:10.1007/s10462-009-9105-x.

Zhou, Z., Zhao, F., Wang, J., 2011. Agent-Based Electricity Market Simulation With Demand Response From Commercial Buildings. IEEE Transactions on Smart Grid 2, 580–588. doi:10.1109/TSG.2011.2168244.

Working Paper Series in Production and Energy

recent issues

No. 44 Fritz Braeuer, Rafael Finck, Russell McKenna: Comparing empirical and model-based approaches for calculating dynamic grid emission factors: An application to CO_2-minimizing storage dispatch in Germany

No. 43 Russell McKenna, Jann Michael Weinand, Ismir Mulalić, Stefan Petrović, Kai Mainzer, Tobias Preis, Helen Susannah Moat: Quantifying the trade-off between cost-efficiency and public acceptance for onshore wind

No. 42 Thomas Dengiz, Patrick Jochem, Wolf Fichtner: Demand response through decentralized optimization in residential areas with wind and photovoltaics

No. 41 Jann Michael Weinand, Fabian Scheller, Russell McKenna: Reviewing energy system modelling of decentralized energy autonomy

No. 40 Jann Michael Weinand, Sabrina Ried, Max Kleinebrahm, Russell McKenna, Wolf Fichtner: Identification of potential off-grid municipalities with 100% renewable energy supply

No. 39 Rebekka Volk, Christian Kern, Frank Schultmann: Secondary raw material markets in the C&D sector: Study on user acceptance in southwest Germany

No. 38 Christoph Fraunholz, Dirk Hladik, Dogan Keles, Dominik Möst, Wolf Fichtner: On the Long-Term Efficiency of Market Splitting in Germany

No. 37 Christoph Fraunholz, Dogan Keles, Wolf Fichtner: On the Role of Electricity Storage in Capacity Remuneration Mechanisms

No. 36 Hansjörg Fromm, Lukas Ewald, Dominik Frankenhauser, Axel Ensslen, Patrick Jochem: A Study on Free-floating Carsharing in Europe – Impacts of car2go and DriveNow on modal shift, vehicle ownership, vehicle kilometers traveled, and CO_2 emissions in 11 European cities

No. 35 Florian Zimmermann, Andreas Bublitz, Dogan Keles, Wolf Fichtner: Cross-border effects of capacity remuneration mechanisms: the Swiss case

No. 34 Judith Auer: Ladeinfrastruktur für Elektromobilität im Jahr 2050 in Deutschland

No. 33 Jann Weinand, Max Kleinebrahm, Russell McKenna, Kai Mainzer, Wolf Fichtner: Developing a three-stage heuristic to design geothermal-based district heating systems

No. 32 Daniel Fehrenbach: Modellgestützte Optimierung des energetischen Eigenverbrauchs von Wohngebäuden bei sektor-gekoppelter Wärmeversorgung –Vorstellung des POPART-Modells

Impressum

Karlsruher Institut für Technologie

Institut für Industriebetriebslehre und Industrielle Produktion (IIP)
Deutsch-Französisches Institut für Umweltforschung (DFIU)

Hertzstr. 16
D-76187 Karlsruhe

KIT – Universität des Landes Baden-Württemberg und
nationales Forschungszentrum in der Helmholtz-Gemeinschaft

Working Paper Series in Production and Energy
No. 45, July 2020

ISSN 2196-7296