Energy Reports 12 (2024) 5268–5279

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

Applying machine learning to electricity price forecasting in simulated energy market scenarios

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ARTICLE INFO

Keywords:
Electricity price forecasting
Machine learning
Agent-based modelling
Energy systems analysis

ABSTRACT

Policy packages, such as the "European Green Deal", call for a substantial restructuring of the power plant park. This, in combination with more flexible demand, will result in novel electricity price dynamics. These can be studied using, e.g., agent-based models which simulate bidding decisions of market actors, thereby uncovering emergent market phenomena. For their bidding decisions, simulated actors – just like real-world actors – require accurate market price forecasts. Techniques to obtain such forecasts need to be applicable to vastly different future electricity market scenarios, ideally without the need of scenario-specific retraining. This is a major difference compared to real-world electricity market forecasting, which is based on minimal variations in the underlying energy system. Despite the long track record in this field, it is not sufficiently clear which methods are suitable for forecasting simulated future electricity markets in greatly varying scenarios and technology mixes. To address this gap, we assess the applicability of different forecasting techniques to price time series generated by simulations of the future electricity market. We then evaluate the forecast accuracy of two recent machine learning architectures, namely N-BEATS and Temporal Fusion Transformers, based on parameter combinations with significant expansions of renewable energy and flexibility option capacity. As expected, the results demonstrate that machine learning exhibits superior accuracy compared to naïve benchmarks. Particularly, when future covariates, such as residual load, are employed, the mean absolute error consistently remains below 1.40 EUR/MWh. This may be attributed to reduced inner complexity of simulated electricity prices compared to real-world market dynamics. Our findings demonstrate that machine learning can provide reliable forecasts of future electricity prices and that retraining may not be necessary even with widely varying shares of renewable energy and flexibility capacity. These forecasting methods could therefore be effectively employed in electricity market simulations in the context of the energy transition.

1. Introduction

In order to make well-informed decisions and to develop effective legislation, investors and policy makers require a comprehensive understanding of the electricity market, including its future developments. This is particularly important in the context of significant changes being introduced by the ongoing energy transition. New legislation, exemplified by the "European Green Deal" (European Commission, 2021), defines a transformation of the energy system that will diverge from the status quo in a number of significant ways. These changes include a transition towards high shares of variable renewable energy (RE) sources and a substantial increase in flexibility options such as battery storages and demand-side flexibility technologies. These developments are already influencing the current market environment and will also have an increasing impact on future electricity markets, resulting in novel price dynamics (Haugen et al., 2024).

Scenarios of the energy transition can be simulated by applying, e.g., agent-based modeling (ABM), which is a promising approach in this field of study (Pfenninger et al., 2014). ABM enables researchers to identify and analyze the market dynamics that result from the decisions of individual market actors. In order to formulate these decisions and optimize their operational schedules, agents require forecasts of

Abbreviations: ABM, Agent-based modeling; LSTM, Long short-term memory model; MAE, Mean absolute error; MAPE, Mean absolute percentage error; ML, Machine learning; NN, Neural network; PV, Photovoltaics; RE, Renewable energy; RMSE, Root mean squared error; TFT, Temporal fusion transformers.

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https://doi.org/10.1016/j.egyr.2024.11.013
Received 22 August 2024; Received in revised form 22 October 2024; Accepted 4 November 2024

electricity prices. This problem falls within the domain of time series forecasting, a well-established area of research with a rich history. A considerable body of research and the increasing computational power have led to the development of a wide range of approaches, from simple techniques to highly sophisticated machine learning (ML) methods (Petropoulos et al., 2022). However, existing studies have largely focused on past and present energy systems, and there is a clear need for research that explicitly integrates the significant changes associated with the energy transition.

What is therefore required is a robust and comprehensive approach to forecasting electricity prices that can be applied across diverse energy transition scenarios. This solution must ensure accuracy and consistency, while maintaining a reasonable level of preparation and execution time. For this purpose, we investigate and combine two areas of research, electricity market simulation and time series forecasting, with a particular focus on ML. This integration is intended to facilitate the generation of robust results even in scenarios characterized by a significant increase in RE sources and novel price dynamics.

1.1. Related works

A comprehensive review on electricity price forecasting was carried out in Weron (2014) describing the special nature of electricity as a commodity. Especially in the recent past, an extensive number of reviews has been published (Jiang and Hu, 2018; Jedrzejewski et al., 2022; Tschora et al., 2022; Heidarpanah et al., 2023; Xiong and Qing, 2023; Jiang et al., 2023; Lehna et al., 2022). Probabilistic electricity price forecasting is extensively reviewed in Nowotarski and Weron (2018). The recent work of Beltrán et al. (2022) proposes a framework for day-ahead electricity price forecasts using statistical methods and neural networks (NN) enforcing the human-machine collaboration. In Beran et al. (2021), hybrid models, specifically combined fundamental and econometric models, are found to be best suitable for day-ahead to week-ahead electricity prices, the relevant range for most operational decisions and strategy optimization. Transfer learning is tested in Gunduz et al. (2023) demonstrating an improved performance compared to a single-market procedure. Besides standard statistical methods (e.g., autoregressive moving-average models), NN and especially deep learning are gaining more popularity due to higher availability of computational power (Akhtar et al., 2023).

As the shares of RE in the electricity mix increases, the electricity price is increasingly influenced by fluctuations in solar irradiation and wind speed (Alkhayat and Mehmood, 2021; Meng et al., 2022). This highlights the need for adaptations in forecasting approaches to account for these variables (Nyangon and Akintunde, 2024). Expected load and RE generation are highly relevant for accurate electricity price forecasts (Billé et al., 2023; Bai, 2024; Da Silva and Meneses, 2023; Alhendi et al., 2023; Bashir et al., 2022). Regarding solar irradiation time series, the application of neural networks is prominent by applying long short-term memory (LSTM) networks (Cheng et al., 2021), hybrid deep NN combing multivariate inputs (Huang et al., 2021). Further, the solar power generation potential is also of high interest to market participants and modelers (Ledmaoui et al., 2023). For this, also LSTM networks are applied to forecast the expected generation by integrating domain knowledge explicitly for photovoltaics (PV) (Qu et al., 2021). Forecasting approaches are developed to be used even when no sufficient meteorological data is available by using data from other surrounding PV stations (Zhen et al., 2021). Looking at the area of wind forecasts, we also find a wide range of approaches (Arslan Tuncar et al., 2024), such as combining statistical methods with NN (Camelo et al., 2018) or temporal-based transformer (Mo et al., 2024). Nazir et al. (2020) give an extensive overview of different wind forecasting methods with increasingly popular NN integrations. Sewdien et al. (2020) identified critical parameters in NN for wind generation forecasting concluding that longer forecast periods require larger and more layers in the NN. Focusing on the trading aspect of wind generation, Fan et al. (2009) apply a two-stage NN, whereas Cruz et al. (2011) confirm an influence of wind generation forecasts on price forecasts when analyzing the situation in Spain. Fraunholz et al. (2021) combine forecasts based on ML within an ABM demonstrating that the NN approach outperforms linear regression and naïve benchmarks in a European case study from 2020 to 2050. In Shimomura et al. (2024), explainable artificial intelligence is employed to evaluate the impact of RE sources on electricity prices in Japan. In Castilho Braz et al. (2024), the Brazilian electricity markets are the subject of a detailed analysis, with forecasts of price trends for both the day-ahead and Intraday markets. Walter and Wagner (2024) present a generative time series simulation for day-ahead electricity prices on an empirical study on the EPEX spot market in Europe in the years 2020–2023. In order to forecast electricity prices in the Hungarian market, an extensive data set comprising more than 40 years of meteorological data has been applied in Mayer et al. (2023).

The majority of these studies share a common characteristic: they present extensive training, testing, and validation of their models on rich historical data, but with little variation in the underlying electricity system. This represents a significant limitation in the analysis of energy transition scenarios, given that electricity price dynamics will be fundamentally different in future electricity markets with high shares of variable RE.

1.2. Novelty

In order to address the shortcomings of existing research, which is closely associated with past and current energy system dynamics, we propose a novel assessment of various forecasting techniques. The approach is based on the combination of advanced ML with an ABM capable of generating electricity price training data sets for a range of potential future electricity systems. This setup allows us to investigate novel electricity price dynamics. Notably, RE technologies are progressively replacing conventional power plants, with fuel-based technologies projected to be gradually phased out in the coming years. The rising prevalence of RE is expected to have considerable influence on electricity prices, given that RE are characterized by almost negligible marginal costs and that conventional power plants are losing their role in price formation. Moreover, the expanded integration of flexibility options, such as battery storage, will significantly impact the energy system. Consequently, we employ the state-of-the art ABM electricity market simulation AMIRIS (Schimeczek et al., 2023a). Specifically, AMIRIS is parameterized to simulate a range of potential future electricity market scenarios which are then transformed into extensive training and testing data sets. While we acknowledge that simulated data cannot fully replicate all nuances present in measured data, it is recognized that it offers a valuable and innovative additional perspective. For example, Frey et al. (2020) have already identified the emergence of new price dynamics resulting from transformative shifts observed in such electricity market simulations. The objective of our research is, therefore, to gain a more comprehensive understanding of the accuracy and performance of varying electricity price forecasting methods in evolving renewable-based electricity markets.

1.3. Paper structure

The paper is structured as follows. In Section 2, we present an overview of agent-based energy market simulation and describe the open electricity market model AMIRIS in. In Section 3, we provide background information on electricity markets. Subsequently, five forecasting methods are described, ranging from naïve benchmarks to advanced ML methods. The necessary training and testing data is generated by AMIRIS. In Section 4, we assess the implemented approaches in terms of their quantitative forecasting accuracy. In Section 5, we discuss the practical applications and constraints of the aforementioned methods, with particular consideration given to the perspective of electricity market simulation models. Finally, in Section

6, we give a summary of the findings and outline remaining open questions.

2. Material and methods

In this Section, we argue why ABM is a powerful method to investigate future electricity markets. Subsequently, we present the ABM AMIRIS, which is applied in this study, and we provide an overview of the model design and architecture. Finally, we argue the suitability of AMIRIS for generating training and testing data for the ML networks.

2.1. Agent-based energy market simulations

The liberalization and the growing complexity of energy markets over the last decades brought new challenges to energy systems modelers (Pfenninger et al., 2014). The growing field of ABM can help researchers to find answers to pressing questions of today's and tomorrow's complex energy systems (Klein et al., 2019). Especially when simulating electricity markets, ABM have proven to be a well suitable method (Farmer et al., 2015; Ringler et al., 2016; Deissenroth-Uhrig et al., 2017; Barazza and Strachan, 2020). Firstly, by incorporating the perspective of individual actors, researchers gain insight into possible emergent effects stemming from individual agents' actions causing macro-level phenomena (Frey et al., 2020). Secondly, employing heterogenous agents in an ABM simulation allows for the representation of diverse actor characteristics, including their objectives, risk profiles, information levels, and interactions with their environment (Kraan et al., 2018). Thirdly, the practical applicability of ABM in addressing real-world energy transition challenges, while maintaining computational feasibility, stands as a significant advantage over game theoretical approaches, which may become intractable when parameterized for tackling substantial real-world problems (Hansen et al., 2019). It is highly important to accurately represent agents and their environment in an ABM. Besides detailed actors' studies (Reeg, 2019), the agent's interactions have to be modelled with a high level of detail. The central element of these economic models is the simulated day-ahead electricity market where a market clearing is carried out periodically. In order to participate in the market, an agent has to submit its bids and asks to the market. To this end, the agent is equipped with decision making mechanisms that account for different qualities of strategic decisions (Guerci et al., 2010; Li, 2012). Since agents typically act on expected prices, accurate electricity price forecasts are critical for the simulation and performance of such agents.

In the realm of energy systems analysis, models must acknowledge the complex interplay of social, technological, economic and environmental dimensions (Bale et al., 2015). ABM are well-suited in examining the interactions and behaviors of diverse actors, accounting for market imperfections (Weidlich and Veit, 2008; Ragwitz et al., 2007). Notably, there are several (open) ABM, such as AMIRIS (Schimeczek et al., 2023a), ASSUME (Harder et al., 2023), BSAM (Kontochristopoulos et al., 2021), EMLab-Generation (Chappin et al., 2017), MASCEM (Vale et al., 2011), and PowerACE (Sensfuß, 2008).

2.2. Electricity market modelling using AMIRIS

We deploy the open ABM AMIRIS which is the "Agent-based Market model for the Investigation of Renewable and Integrated energy Systems" (Schimeczek et al., 2023a). AMIRIS has been developed since 2008 and was published open source[1] in late 2021 (Nienhaus et al., 2021). It is a powerful simulation tool based on the framework FAME (Schimeczek et al., 2023b; Nitsch et al., 2023a) and it is used for the analysis of energy policy instruments and market integration of RE and flexibility options. The heart of the model is the simulation of the day-ahead electricity market revealing market dynamics and agent interactions (Nitsch et al., 2021a) while considering different policy frameworks (Frey et al., 2020). In Klein et al. (2019), a detailed comparison of AMIRIS with two other ABM contrasting a state-of-the art optimization model is carried out. AMIRIS has been back-tested for the day-ahead electricity markets of Germany (Maurer et al., 2024) and Austria (Nitsch et al., 2021b) which resulted in a good fit of simulated and historical electricity prices. Fig. 6 in the Appendix provides an overview of the agents represented in AMIRIS (i.e. power plant operators, traders, flexibility marketers, markets, and regulators) and their interactions via information, energy, and money flows. Users have to define and provide the input data, keeping feature selection and the identification of relevant time series in mind (Müller, 2021). In the context of AMIRIS this translates to power plant park structure, RE generation time series, demand data, and operational cost data. Flexibility options apply one of two distinct strategies when participating in the day-ahead electricity market: maximizing their own profits or minimizing system dispatch costs (Nitsch et al., 2024). These strategies represent a business-centered optimum or a system-friendly approach to dispatch the storage. Further revenue streams for flexibility options, such as Intraday markets, are currently under development.

In our analysis, we will use data derived from AMIRIS to test different forecasting approaches. This offers many key advantages: i) we generate training and testing data matching our needs to feed the NN, ii) we are in full control over the level of complexity in each scenario by defining agents and their properties individually, iii) we are able to assess the impact of changing power systems on price dynamics and test the suitability of different forecasting methods, iv) we demonstrate the use-case of applying different ML architectures in an electricity market simulation model, and v) we extract the key learnings of integrating the presented ML approaches in order to provide benefits for other electricity market simulation model in the field. The detailed procedure of the scenario definition is described in Section 3.2.

3. Theory and calculation

We present the theory behind wholesale electricity markets in Section 3.1. This includes a brief summary of changing price dynamics introduced by growing RE shares and impacts by large flexibility option capacity which will likely be installed in the (near) future. Based on the theory, Section 3.2 outlines our scenario definitions while Section 3.3 describes the models tested to forecast electricity prices.

3.1. Fundamental aspects of electricity markets

Wholesale electricity prices are the market result of matching supply of producers (i.e. power plant operators) and demand of consumers in a dedicated market zone. Besides trading at the power exchange, consumers and producers can also agree on individual over-the-counter trades. Although, these trades are usually non-transparent and bilateral, we assume them to be mostly aligned with wholesale prices, since larger price spreads would resemble arbitrage opportunities. Beyond that, there are also dedicated markets which are designed for ancillary services, e.g., frequency restoration reserves, usually with pay-as-bid schemes (Aussel et al., 2017). In reality, these markets do have implications on the wholesale markets since they impact the available capacity, however, they are currently not in the focus of the AMIRIS simulation. Consequently, similar to futures and forwards markets, they are not included in our day-ahead electricity price forecasting process but may be considered in extensions to our work. The main instrument to determine electricity prices is the day-ahead spot market where a market clearing is carried out (Martin et al., 2014). Bids and asks are sorted resulting in a merit-order. In Central Europe, a uniform pricing mechanism is established in the day-ahead electricity markets (Zakeri et al., 2023). Our model is therefore also based on this form of pricing. For the clearing, a congestion-free nature of the market and

[1] https://gitlab.com/dlr-ve/esy/amiris (accessed on 30 October 2024)

decentralized dispatch are assumed.

In accordance with economic theory, market participants define their bids according to their marginal cost. This mainly includes operational costs, fuel costs, and emission certificate costs. In reality, non-convex costs (Makkonen and Lahdelma, 2006) can lead to uplifts, i.e. markups to marginal costs accounting for ramp-up costs (Liberopoulos and Andrianesis, 2016), and downlifts, i.e. markdowns accounting for ramp-down costs (Pape et al., 2016). AMIRIS can also consider such markups or markdowns.

3.2. Energy transition scenarios

We define two main sets of scenarios. Firstly, we vary the storage capacity within four distinct electricity market configurations, reflecting different degrees of market influence by these flexibility options. Secondly, we examine the expansion of RE in terms of PV and wind onshore installations. This approach is designed to yield insights into forecasting accuracy in scenarios with different combinations of RE shares. It is essential to note that both sets of scenarios should be viewed as parameter variations rather than being interpreted as definitive, sophisticated scenarios, roadmaps, or guidelines for shaping future electricity markets.

Regarding the variation of flexibility option capacity, such as battery storage systems (Divya and Østergaard, 2009), we define four distinct scenarios in Table 1. "*No Flex*" describes an artificial electricity system where the power plant park solely consists of controllable conventional power plants and fluctuating renewable power plants. Due to the idealized way of modelling renewable power generation by applying exogenously defined time series, we expect a highly correlated situation between residual load (i.e. load which has to be met by dispatchable and typically conventional power plants) and the day-ahead electricity price. This is also the reason why we do not consider a conventional-only scenario.

When we introduce flexibility options, see "*Little Flex*", we expect to observe a more complex pattern due to the impacts of flexibility options. Initially, we will keep their share relatively small and increase it in "*Mid Flex*" up to "*High Flex*" so that we can evaluate the capabilities of the forecasting algorithms. Simple forecasting methods most likely will not perform well in the latter two settings, because the operational decisions by flexibility options decouple the idealistic residual load and price relationship. The remainder of the system consists of a load agent fulfilling its electricity demand, a day-ahead electricity market agent performing an hourly market-clearing, as well as supply traders offering their generation capacity at their marginal costs. The installed power plant capacity is approximately aligned with the German market in 2019 (Nienhaus et al., 2023) whereas load and RE generation potential are derived from 2018 and 2019 (SMARD, 2020). In all four scenarios, the RE capacity is identical and based on historical values. This implies that potential future scenarios with higher RE shares and potentially different price dynamics are currently not considered.

While the scenarios presented so far only consider different shares of flexibility options, we also compile scenarios of RE expansion which provide additional insights of forecasting performance. For this purpose, the AMIRIS scenario generator *scengen* (Nitsch et al., 2023b) was used to generate more than 100 scenarios which are processed to training and testing data sets. In each scenario, PV and wind onshore capacity is randomly chosen within a predefined range. All other parameters roughly correspond to the German electricity system in 2019 (Nienhaus et al., 2023). All input data undergoes a thorough check for outliers and is subsequently normalized to facilitate the ML process.

3.3. Investigated forecasting methods

In total, we compare five forecasting methods with varying levels of complexity, two comprehensive ML architectures and three benchmarking methods. N-BEATS (Oreshkin et al., 2019) is a NN for time series forecasting by applying deep learning. It is well tested on data sets used in forecasting competitions and is said to be applicable on a wide range of domains. Temporal fusion transformers (TFT) (Lim et al., 2021) allow to integrate past and also future covariates in their training. This is a significant advantage over many other methods promising better forecasting performance. Seasonal and trend characteristics can be embedded by temporal features within the input data and the model's ability to encode such information directly. In our application, integrating covariates into the training process is expected to enhance forecasting performance, see also Fig. 1. Past and future covariates describe time series that are available for the past and future, respectively. Examples of such time series include time and calendar information. Additionally, historical covariates, which are only available for past time steps, may be included in the model. These could include, for example, actual renewable energy generation. A detailed preliminary study on feature selection was carried out in Nitsch and Schimeczek (2023). The impact of varying train-test splits, ranging from 75 % to 25 % and 25–75 %, was evaluated.

In order to quantify the accuracy, a set of commonly used day-ahead electricity price forecasting methods is employed as a benchmark (Hyndman and Athanasopoulos, 2018). Namely, we apply the naïve benchmark

$$\hat{p}_{T+h|T} = p_T \quad (1)$$

where the forecasted day-ahead electricity price $\hat{p}$ at the time $T+h$ is set equal to the day-ahead electricity price p at time T (Hyndman and Athanasopoulos, 2018). A slight modification involves setting

$$\hat{p}_{T+h|T} = p_{T+h-24} \quad (2)$$

where the forecasted day-ahead electricity price is derived from the day-ahead electricity price p at time $T+h-24$, taking into consideration the daily price patterns (Hyndman and Athanasopoulos, 2018). Additionally, we deploy an Exponential Smoothing (Winters, 1960; Holt, 2004) as

$$\hat{p}_{T+h|T} = \alpha p_T + \alpha(1-\alpha)p_{T-1} + \alpha(1-\alpha)^2 p_{T-2} + \dots \quad (3)$$

with the smoothing operator α, a parameter with values in the range $[0,1]$, which is a simple yet well-proven time series forecasting method applying exponentially decreasing weights over time.

Hyper-parameters were optimized using the state-of-the-art framework Optuna (Akiba et al., 2019). The model code and documentation can be found in the open repository *focapy* (Nitsch, 2023). For error metrics, we calculated mean absolute errors (MAE) as

Table 1
Overview of scenarios distinguished by different flexibility option capacity.

Scenario	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*
Parameter				
Electricity demand	527 TWh/a			
Conventional capacity	77 GW			
Renewable capacity	120 GW			
Flexibility options	0 GW	4 GW	20 GW	80 GW

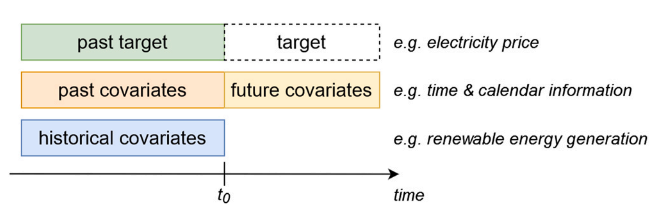

Fig. 1. Past and future covariates as time series inputs to TFT.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|a_t - \widehat{p}_t| \tag{4}$$

where a and $\widehat{p}$ represent the actual and forecasted prices, respectively, with a total length of T. We chose an absolute error metric, such as MAE, given the potential for target values (electricity prices) to be (close to) zero or even negative, making the use of mean absolute percentage errors (MAPE) problematic. Additionally, we calculated root-mean-squared errors (RMSE) as

$$RMSE = \sqrt{\{\frac{1}{T}\sum_{t=1}^{T}(a_t - \widehat{p}_t)^2\}} \tag{5}$$

4. Results

We begin by examining the results of the AMIRIS scenarios with different shares of flexibility options followed by the results of forecasting accuracy in scenarios of RE expansion.

4.1. Different shares of flexibility options

Prior to presenting the results of the forecasting methods in Section 4.1.2, we analyze the simulation runs of the four scenarios. These results offer valuable background information that aids in interpreting the forecasting accuracy.

4.1.1. Impact on market dynamics

Fig. 2 shows day-ahead electricity prices as simulated by AMIRIS over a 168-hour period, with each line representing one of the four scenarios (essentially varying the amount of flexibility options available). Increasing storage capacity generally has a dampening effect on electricity prices. In particular, price peaks can be flattened by discharging storage, while valleys can be raised by charging storage. It is important to note that the storage operator aims to maximize its profits, while taking into account its impact on electricity prices when optimizing its bidding schedule. As a result, there are certain time periods when all four curves are aligned, indicating that during these hours the storage operator either has no significant impact on the resulting electricity prices, or is simply inactive.

The statistics in Table 2 provide an understanding of the variability of electricity prices under different assumptions of storage installations, highlighting the impact of flexibility on pricing dynamics. In "*No Flex*", there is a relatively wide dispersion of prices, as indicated by the standard deviation of 15.27 EUR/MWh. The minimum price[2] is −63.51 EUR/MWh, while the maximum is 116.83 EUR/MW. Moving to "*Little Flex*", the mean price increases slightly to 38.49 EUR/MWh, accompanied by a lower standard deviation of 13.75 EUR/MWh, indicating a narrower spread of prices compared to "*No Flex*". In "*Mid Flex*", the mean price rises further to 38.80 EUR/MWh, with a continued decrease in the standard deviation to 12.07 EUR/MWh, suggesting the previously described price dampening effect. Finally, in "*High Flex*", the mean price reaches 38.96 EUR/MWh, accompanied by the lowest standard deviation of 11.17 EUR/MWh among all scenarios. The results from the year 2018 demonstrate similar overall trends as found for the year 2019. However, differences arise in the weighted mean electricity prices amounting to 43.50 EUR/MWh in 2018 and 38.50 EUR/MWh in 2019.

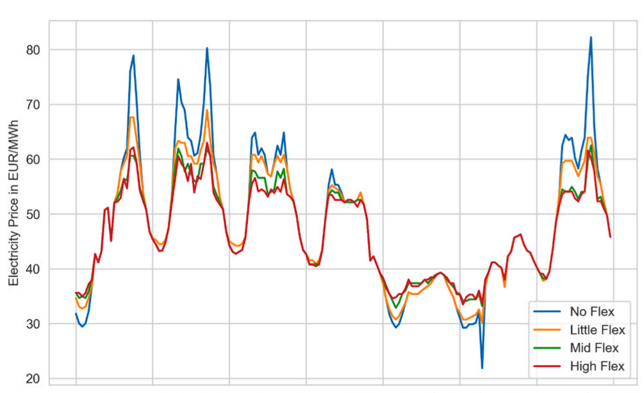

Fig. 2. Price dampening effect of different flexibility capacity in the four scenarios on simulated electricity prices over a one-week period in November 2019.

4.1.2. Electricity price forecasting accuracy

The two ML methods N-BEATS and TFT are trained on 2018 and tested on 2019. For the evaluation of the forecasting accuracy, a full year is chunked in roughly 500 samples, each with 168 hours of past covariate data and 24 hours to forecast. Forecasted values are then tested against actual values from the simulation. Table 3 lists MAE of all forecasting methods in the four scenarios.

The MAE provide insights into the forecasting capabilities of each method within different shares of flexibility options. Notably, the TFT trained with future covariates (expected load and RE generation) shows the lowest MAE values, suggesting its superior accuracy in forecasting electricity prices across a spectrum of scenarios. The benchmark methods are performing worse in every scenario, but are much cheaper to apply, since they do not require to train a model. Further, the presented results clearly demonstrate a consistent trend of improved accuracy across the scenarios of "*No Flex*" to "*High Flex*". We conclude that this effect is likely due to the price flattening effect of increasing market impact of flexibility options, see also Fig. 2.

Fig. 3 displays an exemplary forecast made by the TFT model in "*Mid Flex*". Overall, the forecast aligns well with the actual price dynamics. Nevertheless, there is a slight deviation as the model fails to accurately forecast the first valley underestimating actual values. This can likely be attributed to price dynamics caused by charging actions of flexibility options. Forecasting errors also exhibit a temporal dependency that correlates with the load pattern. Consequently, accuracy tends to be best at night, with errors peaking during the day (Nitsch and Schimeczek, 2023). In the context of the German case study presented, local weather effects, including short-term fluctuations in renewable energy generation, generally have a limited impact on the day-ahead market zone and are therefore not of great influence to this particular forecasting procedure.

4.2. Forecasting accuracy in future energy scenarios

As elaborated in the Introduction in Section 1, the energy transition will bring very different market dynamics compared to historical observations. Besides the expanding flexibility potential, as presented in Section 4.1, we expect considerable impacts by the expansion of RE leading to novel price dynamics of electricity markets. Therefore, we investigate the effects on forecasting accuracy in such scenarios. For this we have created unique training and testing data, as described in Section 3.2. Due to high computational costs of ML training, we have limited this analysis to TFT, the best performing method so far. Fig. 4 shows the results of different train-test splits in two model configurations (without future covariates and with future covariates). All six models are trained and evaluated independently. The left column shows the available training data to the TFT model and their weighted mean average prices

[2] Periods of high inflexible generation and low demand can lead to negative prices in electricity markets.

Table 2
Descriptive statistics on simulated electricity prices in the four scenarios.

Year	2018				2019			
Scenario	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*
Metric								
Std. dev.	15.48	13.56	11.95	11.07	15.27	13.75	12.07	11.17
Minimum	−35.21	−22.11	−17.18	0.00	−63.51	−52.49	−37.73	0.00
Maximum	115.96	103.38	95.16	94.78	116.83	102.15	96.33	96.33

Table 3
Mean absolute error (MAE) in EUR/MWh of forecasts in four different scenarios.

Scenario / Metric	*No Flex*	*Little Flex*	*Mid Flex*	*High Flex*
Naïve t_1 (1)	9.29	7.78	6.76	6.45
Naïve t_{24} (2)	8.57	7.54	6.27	5.91
Exponential Smoothing (3)	8.06	6.70	5.73	5.46
N-BEATS (Oreshkin et al., 2019)	7.15	6.24	5.38	5.12
TFT (Lim et al., 2021)	4.11	3.90	3.20	3.26
TFT with future covariates (Lim et al., 2021)	3.12	3.45	3.26	2.86

of the scenario marked with 'x'. Values in between are interpolated by a cubic method. It is evident that as RE capacity increases, electricity prices tend to decrease – a trend consistently observed across all three rows representing different numbers of scenarios and train-test splits (10 scenarios, 30 scenarios, and 90 scenarios). The middle and right column show the forecasting accuracy evaluated as MAE over all errors of the forecasted electricity prices against the actual electricity prices as calculated by AMIRIS. In the middle column, the TFT relies solely on past covariates, while in the right column, the TFT also incorporates future covariates, such as calendar information, expected load, and RE generation.

Notably, we observe a robust results with MAE values ranging from 2.25 to 3.25 EUR/MWh when at least 30 scenarios are employed as training data (middle and bottom rows). However, when restricting training data to only 10 scenarios (top row), forecasting accuracy deteriorates significantly, with MAE doubling, when assessing scenarios that fall well outside the range of known training data. This strongly suggests that the selection of training data is important for the performance of the model. Moreover, the TFT model equipped with future covariates (right column) consistently outperforms the version relying solely on past covariates (middle). Errors are reduced by approximately an order of magnitude, which holds promise for applications in energy system models, particularly ABM. Moreover, in the bottom row, where the train-test split is 75 % and 25 %, the results are similar compared to the middle row, where the split is reversed at 25 % and 75 %.

Additionally, we can observe that MAE generally exhibits a downward trend as onshore wind capacity increases, except for the segment of high wind power capacity, which lacked sufficient training data, as indicated in the top row of plots in Fig. 4. A similar trend is also evident when considering different error metrics like RMSE.

The histograms in Fig. 5 illustrate the distribution of errors for training with 30 and 90 scenarios. It can be observed that an increased number of training scenarios leads to a superior fit when MAE is employed as the error metric. However, the addition of future covariates – a common practice in such forecasting problems (Ozyegen et al., 2022) – improves the accuracy in our analysis even more than the quantity of available training data. Specifically, with such covariate data, MAE remain consistently below 1.40 EUR/MWh.

5. Discussion

As suggested in Haugen et al. (2024), the formation of electricity prices in energy market models represents a significant factor influencing the analysis of actors' behaviour, ranging from the operation of flexibility options to investment decisions. The use of simulated and synthetic data as a complement to historical data is an attractive approach, particularly given its current deployment in the context of creating energy generation and load profiles (Mayer et al., 2023). Consequently, the presented methodology in this paper contributes valuable insights to the currently limited field of such day-ahead electricity price forecasting in high RE penetration scenarios. However, given the inherent complexity and non-linearity of energy markets (Castilho Braz et al., 2024), it is essential to consider that our general conclusions should not be interpreted as individual predictions on market results. Rather, they should be regarded as projections contributing towards a better understanding of potential market dynamics in systems with high shares of RE. Despite the presentation of a comprehensive range of potential scenarios, uncertainty remains to scenario definition and model formulation. Future research should investigate

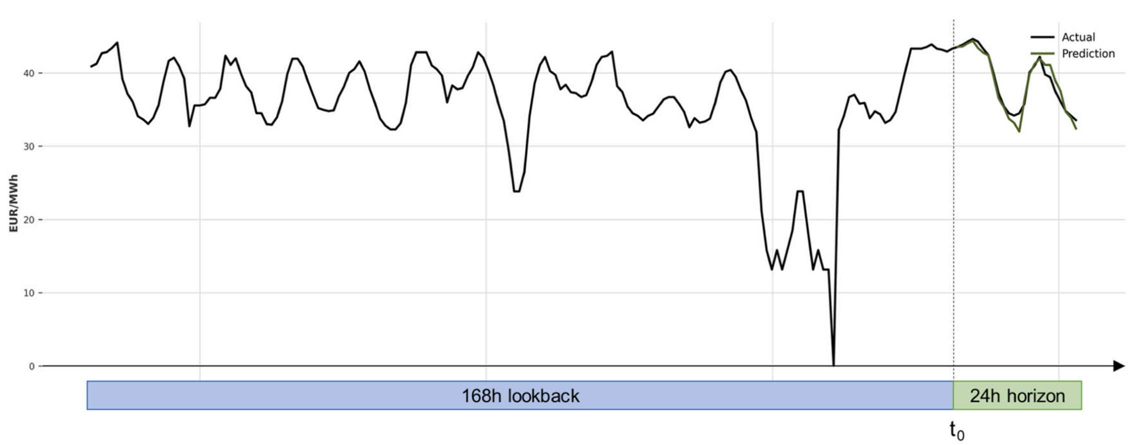

Fig. 3. Exemplary forecasted prices for the next 24 hours (green) by the TFT model in "Mid Flex" with 168 hours of past covariates plotted against actual prices (black).

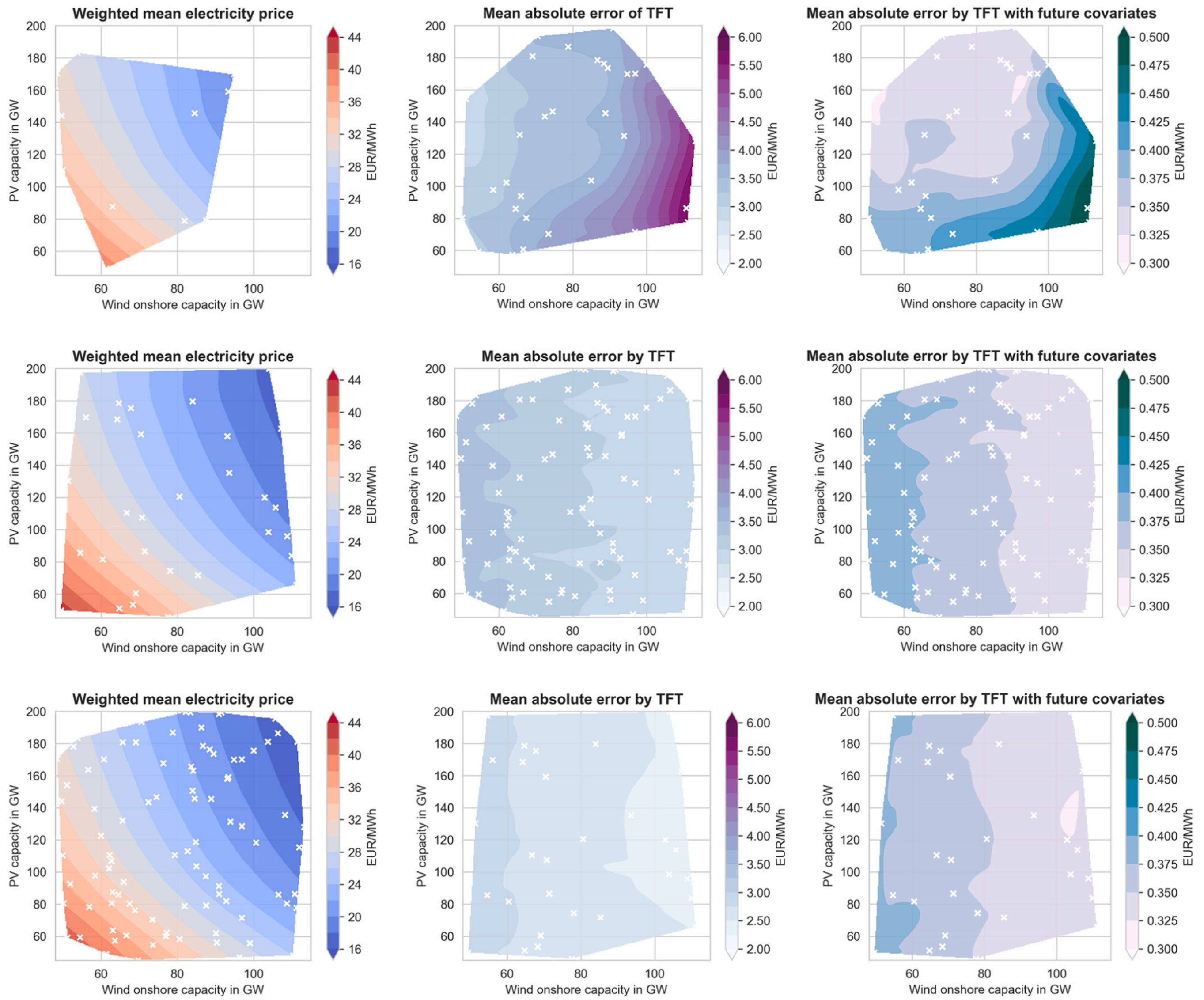

Fig. 4. Simulation of PV and onshore wind expansion scenarios (marked by white 'x' markers) using AMIRIS. Values in between are interpolated using a cubic method. The left column represents the training data, while the other two columns illustrate forecasting accuracy in terms of Mean Absolute Error (MAE) in EUR/MWh. The middle column shows the accuracy based on past covariates alone, whereas the right column includes additional future covariates to the forecasting procedure. Note: Scenarios are considered as parameter variations and shall not be interpreted as definitive and complete future electricity systems, see also Section 3.2.

the influence of changes in market and policy design, unforeseen events with significant impact on energy markets, and the manner in which market actors respond to forecast uncertainty. In addition, we wish to highlight the following limitations.

In the realm of analyzing various flexibility option shares in Section 4.1, it is important to acknowledge a potential limitation related to model training. A possible enhancement lies in the inclusion of a more diverse set of training data to refine the robustness of our models. The analysis of RE expansion in Section 4.2 underscores the considerable impact of the training data selection on results. Future analyses should therefore diligently consider this important aspect. Similarly, within the analysis of RE expansion scenarios in Section 4.2, a notable limitation lies in the missing variability of weather conditions. Periods of low wind and solar generation may substantially impact results, particularly as RE capacity increases. The use of NN with future covariates (as demonstrated in Fig. 4) might mitigate this impact since the network is aware of the short-term residual load. However, without these future covariates, variations in weather years could exert a greater influence on the results. To ensure that our results are easily transferable and understandable, our presented scenarios assume no variation in parameters aside from wind and PV capacity. As already described in Section 3.2, this assumption does not fully capture the real-world dynamics of the energy transition missing the evolution of flexible demand and generation capacity. It is evident that additional markets, which are currently under discussion but not yet implemented, such as capacity or flexibility markets, would influence market dynamics and necessitate further analysis. However, an examination of these points is beyond the scope of the present manuscript.

Beyond these specific limitations, broader considerations should be mentioned. The computational resources and training data allocation significantly affect the time required for training NN. While the initial effort to train models and optimize hyperparameters is substantial, transitioning to the utilization of pre-trained models with optional fine-tuning in production settings could significantly alleviate this workload. When experimenting with a wider array of input features, the explainable feature of TFT could help identify the most influential factors governing forecast accuracy. Additionally, the incorporation of TFT's capability to provide probabilistic forecasts holds the potential to

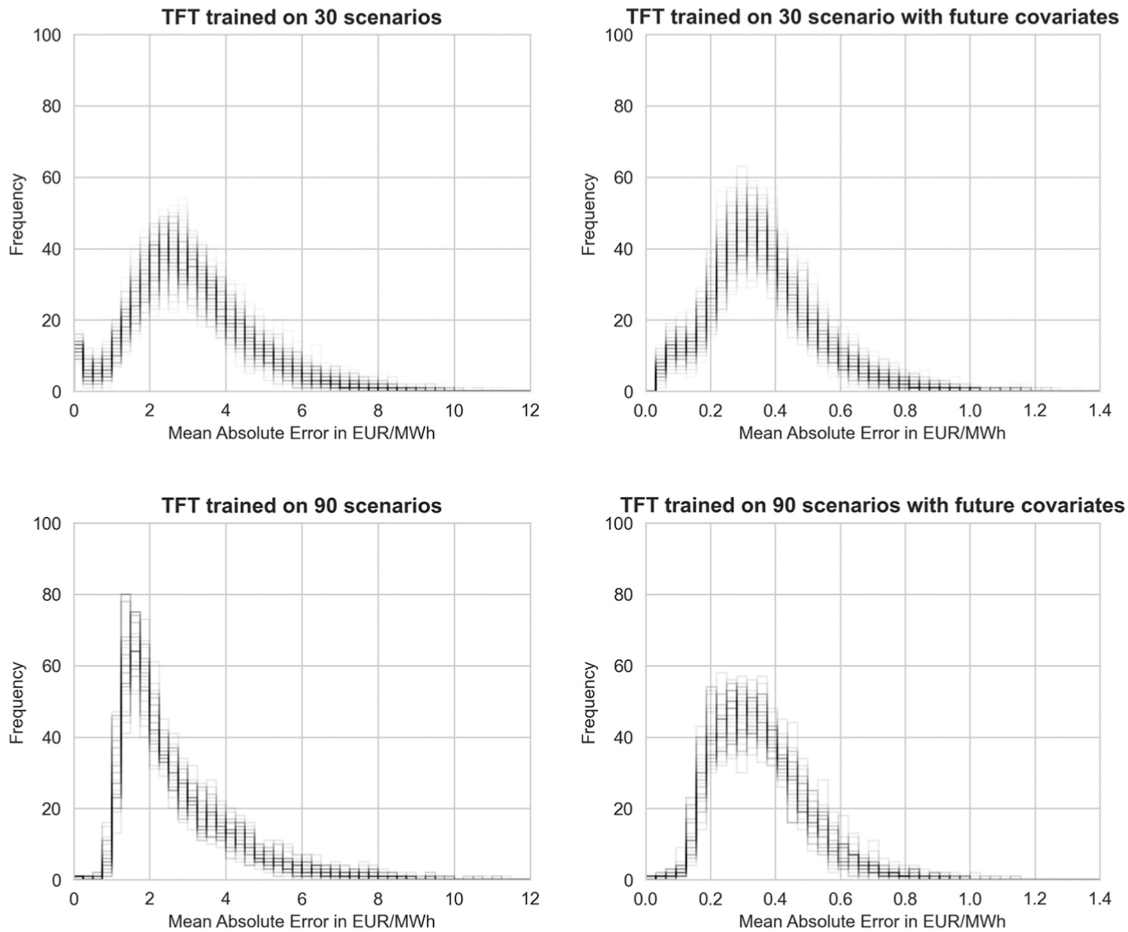

Fig. 5. Distribution of mean absolute error (MAE) in EUR/MWh for different training sets and TFT configurations. Note: Different scaling of x-axis for runs with future covariates.

broaden the applications within energy market simulation models.

In terms of our findings, they align with existing literature as follows: Lago et al. (2021) conducted an extensive review of day-ahead electricity price forecasting, also concluding that deep neural NN, such as TFT, tend to outperform Lasso Estimated AutoRegressive methods, albeit with increased computational costs. Fraunholz et al. (2021) found that NN outperform regression and naïve benchmarks when applied in an ABM. However, the choice of specific architecture significantly influences the results of the ABM, underscoring the need for a careful assessment. Trebbien et al. (2023) presented an analysis of day-ahead electricity prices from 2017–2020, identifying load, wind, and solar generation as key features for an explainable ML model, aligning with our findings regarding input data selection. While our study focuses on TFT networks in a similar domain, it is worth noting that they are often employed in forecasting load (Nazir et al., 2023) or renewable energy generation (López Santos et al., 2022). In contrast to the original N-BEATS architecture (Oreshkin et al., 2019), which does not allow future covariates, the N-BEATSx (Olivares et al., 2023) offers this extension.

Numerical test results show MAE of around 3.30 EUR/MWh on historical German market data. Azam and Younis (2021) conduct load and price forecasting using a novel hybrid deep learning approach demonstrating achieving MAE of around 5.20 USD/MWh on the ISO New England energy market in 2018 and 2019. In Ziel and Weron (2018), twelve distinct historical datasets of day-ahead electricity prices are evaluated, revealing a MAE in the German market zone of approximately 5 EUR/MWh. Fraunholz et al. (2021) perform a scenario analysis of ten interconnected market zones in Europe from 2020 to 2050 with MAPE forecasting errors between 0.10 and 0.39.

6. Conclusion

The findings of our study demonstrate a powerful approach that combines agent-based electricity market simulation and time series forecasting based on machine learning to provide forecasts for energy transition scenarios. Past and present market data, which are widely used in forecasting studies today, do not account for the novel price dynamics of future highly renewable electricity markets. In contrast, we explicitly incorporate foreseeable changes in energy systems resulting from the ongoing energy transition. In particular, we investigate energy transition scenarios with significant expansion of flexibility options and renewable energies, which are used to train and test different forecasting methods. We then use an open state-of-the-art agent-based electricity market model and open data to generate market results in these scenarios that differ significantly from today's energy system. We then assess the accuracy of different electricity price forecasting methods in the context of these widely varying scenarios. In our assessment, comprehensive machine learning methods, namely Temporal Fusion Transformers, demonstrate superior forecasting accuracy for future electricity markets compared to naïve benchmarking methods. Mean absolute errors decrease by approximately one order of magnitude when future covariates are accessible and understandable to the model. In addition to the demonstrated precision, even in environments characterized by significant change, the examined methodologies offer several key advantages over conventional forecasting techniques. Some machine learning-based methods, including Transformers, are capable of handling disparate input data configurations, thereby facilitating their adaptation to evolving settings. Moreover, scaling is readily achievable from simple proof-of-concepts to comprehensive modelling suites. In order to apply our results to other electricity market simulations, modelers need to apply their domain knowledge when defining training data and selecting input features. As machine learning-based methods can be computationally expensive, adequate resources are required, at least during the initial training stage. Our results are relevant not only to agent-based electricity market modelling but also to the broader field of electricity price forecasting. The presentation of quantitative results on forecasting accuracy contributes valuable insights to the general understanding of modeling electricity markets affected by the energy transition. Furthermore, they can be employed to supplement existing assessments of investment decisions within the industrial sector. From a technical perspective, modular, open, and comprehensive software packages facilitate the transferability of our approach to other applications and more in-depth analyses. Future research may address broadening the scenario space, with specific attention to the incorporation of diverse storage agents, varying technological considerations, the influence of potential market powers, and the impact of different agents' operational strategies. It would also be valuable to investigate the uncertainty of future electricity market scenarios in terms of market design and agent behaviour. Furthermore, the presented forecasting technique could also be applied to additional markets, such as Intraday markets. This would facilitate a more comprehensive analysis of the interplay between multiple markets.

CRediT authorship contribution statement

Felix Nitsch: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization**. Christoph Schimeczek:** Writing – review & editing, Supervision, Funding acquisition. **Valentin Bertsch:** Writing – review & editing, Supervision, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Felix Nitsch and Christoph Schimeczek would like to express their gratitude to the German Federal Ministry of Education and Research (BMBF) for their financial support of the FEAT project (grant number 01IS22073B). The authors would like to thank Kristina Nienhaus, Ulrich Frey, A. Achraf El Ghazi, Benjamin Fuchs, and the colleagues from the Department of Energy Systems Analysis at the Institute of Networked Energy Systems, German Aerospace Center (DLR), for their invaluable feedback and insightful discussions on first drafts of the manuscript.

Author agreement statement

We the declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author, Felix Nitsch, is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

Appendix

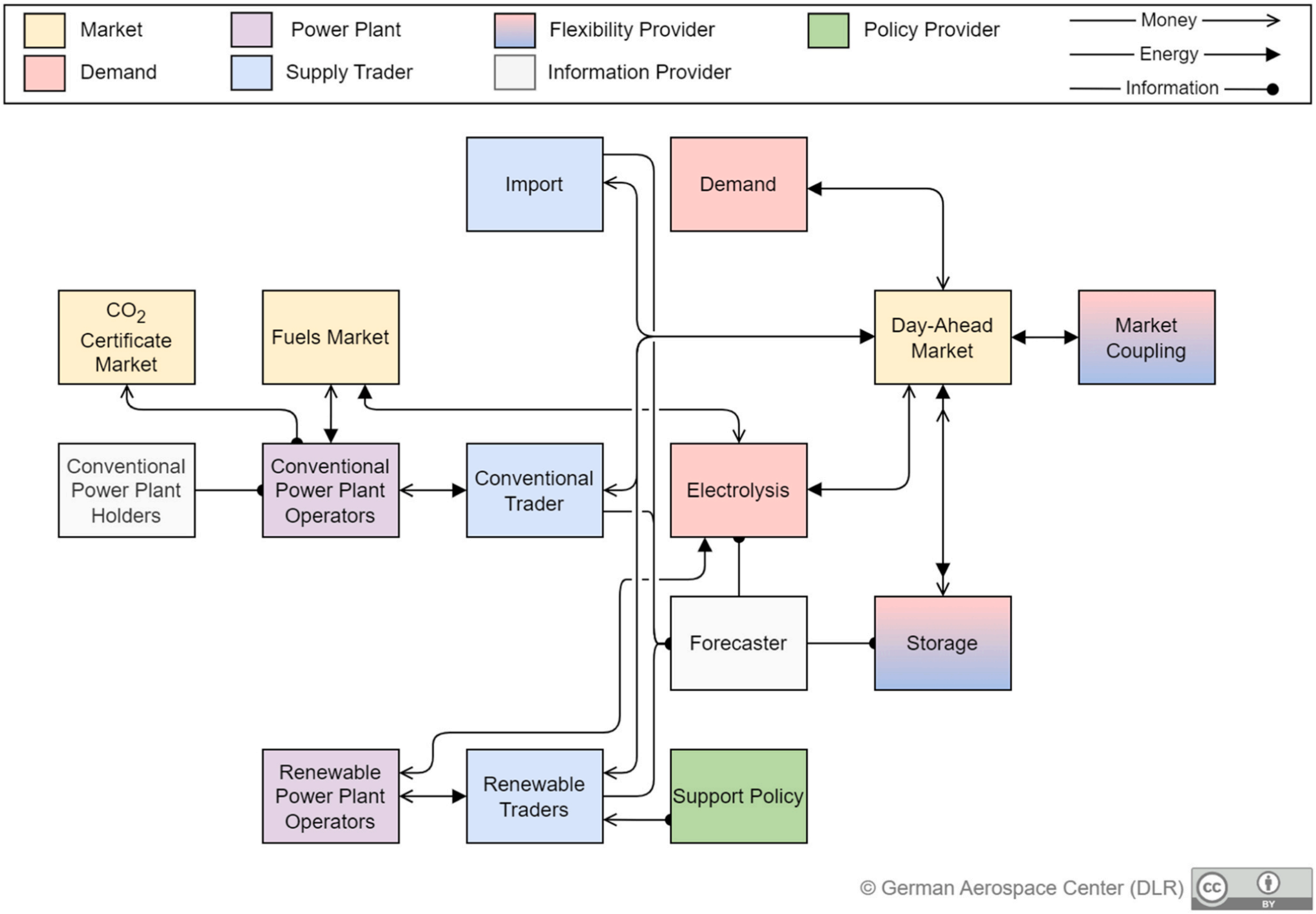

Fig. 6. Schematic overview of the agents and their connections in the agent-based electricity market model AMIRIS (Schimeczek et al., 2023a).

Data Availability

All code used to run this analysis is openly available in Schimeczek et al. (2023a), Nitsch et al. (2023b), Nitsch (2023). The data is based on Nienhaus et al. (2023).

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