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Development of Forecasting Models for German Energy Prices and Carbon Intensity as a Decision Basis for Energy Flexibility Measures

Jonas Wendt*, Arthur Stobert, Jonas Valentin Schulte, Matthias Weigold

Technical University of Darmstadt, Institute of Production Management, Technology and Machine Tools (PTW),
Otto-Berndt-Straße 2, 64287 Darmstadt, Germany
(*Corresponding Author: j.wendt@ptw.tu-darmstadt.de)

ABSTRACT

Energy flexibility measures play a crucial role in the achievement of carbon neutrality. Renewable energy sources can only be prioritized if energy demand can adapt to the supply. For the targeted use of such measures, a better understanding of the energy markets and the affected systems is essential.

The availability of sustainable energy sources is highly dependent on fluctuating environmental conditions like solar radiation or wind speed. Combined with changing energy demand, this leads to volatility in energy prices and carbon intensity. To react to these fluctuations at an early stage, trends in electricity prices and carbon intensities are urgently needed in addition to weather forecasts, which are already available across the board. This gap shall be addressed by this publication, which presents a machine learning based tool to forecast electricity prices and carbon intensities beyond the German day-ahead market for the following 48 hours. Publicly available market data from the past five years was used to train the machine learning model, which achieved a mean absolute error (MAE) of 20.6 €/MWh for day-ahead energy prices during the first half of 2023. The tool forecasts carbon intensities with a MAE of 47.7 gCO2eq/kWh for the same period. The presented forecasting tool enables planning of energy-flexible operating strategies at an early stage and their implementation at industrial sites.

An air conditioning system as an exemplary industrial use case is used to demonstrate the relevance of the presented forecasting model in the context of energy flexibility. The utilization of the forecasting tool and the development of energy-flexible operating strategies resulted in potential savings of 12.33 % in operating costs and 9.94 % in carbon emissions.

Keywords: forecasting models, energy trends, energy flexibility, carbon intensity, climate neutrality

NOMENCLATURE

Abbreviations	
EFM	Energy Flexibility Measure
EFOS	Energy-Flexible Operating Strategy
LEAR	Lasso Estimated Autoregressive
LSTM	Long-Short Term Memory
MAE	Mean Absolute Error
RES	Renewable Energy Sources
TES	Thermal Energy Storage
XGBoost	Extreme Gradient Boosting
Symbols	
$PR(t)$	Day-Ahead Prices (Germany)
$CI(t)$	Forecast of the Carbon Intensity
Δt	Loading Interval of TES
$\dot{Q}(t)$	Cooling Demand
$SOC(t)$	State of Charge of the TES
$C(t)$	Costs
$EER(t)$	Energy Efficiency Coefficient
Indices	
$market$	German Energy Market
$forecast$	Predicted Data
$load$	Loading Phase of TES
$unload$	Unloading Phase of TES
ref	Reference Scenario
$flex$	Energy-Flexible Scenario

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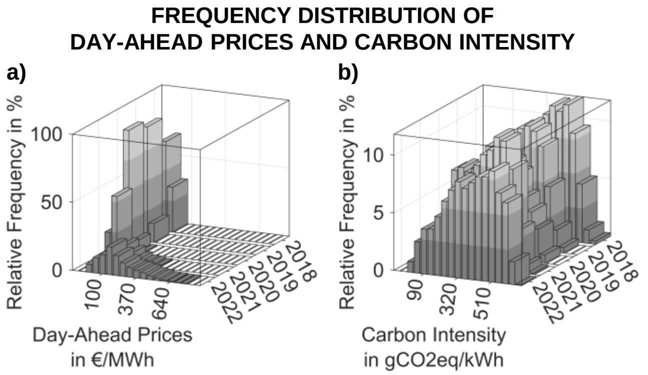

	Day-Ahead Prices in €/MWh				**Carbon Intensity** in gCO2eq/kWh			
	Mean	**Min**	**Max**	**Std**	**Mean**	**Min**	**Max**	**Std**
2018	44.5	-76.0	128.3	17.8	472.0	170.3	731.4	104.7
Δ↓	*-15.3 %*	*18.4 %*	*-5.3 %*	*-12.7 %*	*-15.1 %*	*-14.1 %*	*-13.7 %*	*5.2 %*
2019	37.7	-90.0	121.5	15.5	400.8	146.4	631.1	110.2
Δ↓	*-19.1 %*	*-6.7 %*	***64.7 %***	*12.8 %*	*-6.8 %*	*-18.8 %*	*1.5 %*	*7.6 %*
2020	30.5	-83.9	200.0	17.5	373.4	118.9	640.5	118.5
Δ↓	***217.8 %***	*-17.8 %*	***209.9 %***	*321.0 %*	*13.0 %*	*3.8 %*	*2.2 %*	*-4.2 %*
2021	96.8	-69.0	620.0	73.7	421.9	123.5	654.9	113.6
Δ↓	***143.1 %***	*-72.4 %*	***40.5 %***	*93.8 %*	*6.8 %*	*28.4 %*	*4.5 %*	*7.8 %*
2022	235.4	-19.0	871.0	142.8	450.6	158.6	684.3	122.4

Fig. 1. Results of a data analysis of German electricity market data (a) and carbon intensity (b) for the years 2018 to 2022. Based on data from [1].

1. INTRODUCTION

In recent years, and especially during the 2022 energy crisis, energy prices have increased significantly. In Europe, charges to industry (annual consumption: 2,000 MWh to 20,000 MWh) for electric power doubled on average from 2008 to 2022, ranging from + 34 % in Malta to + 268 % in Greece [2].

When taxes are taken into account, the changes in electricity prices are even greater, as illustrated by a market analysis showing the wholesale prices of the German electricity mix in Fig. 1a. In this context, average prices have risen from 44.5 €/MWh (2018) to 235.5 €/MWh (2022). This corresponds to an increase of 429 %. Looking at the frequency distribution, the increase in the hourly spread is particularly striking increasing from a standard deviation of 17.8 €/MWh (2018) by + 702 % to 142.8 €/MWh (2022).

One factor contributing to increasing volatility in the electricity market is the rising proportion of renewable energy sources (RES) [3]. These sources are directly dependent on highly fluctuating weather conditions. Furthermore, the fluctuating prices of conventional power generation resources and the general bidding tactics employed by market participants in the spot market are additional factors driving the increase in volatility [4]. The high volatility of RES can also be observed by the significant spread of carbon intensities in Fig. 1b. Unlike the behavior of electricity prices, the frequency distribution of carbon intensities has remained relatively constant between 2018 and 2022. The mean intensities have decreased by - 4.5 % from 472.0 gCO2eq/kWh (2018) to 450.6 gCO2eq/kWh (2022). However, the standard deviation has increased by + 16.9 % from 104.7 gCO2eq/kWh (2018) to 122.4 gCO2eq/kWh (2022). The decrease in average intensity coupled with an increase in spread implies an increase in the share of RES electricity generation in gross electricity consumption. According to [5], the share of RES in gross electricity consumption in Germany has risen from 38.7 % (2018) to 46.2 % (2022).

What does this market behavior signify for energy consumers?

Industrial consumers heavily rely on energy prices, as these, multiplied by the energy demand, constitute a substantial portion of the operating costs [6]. One approach to reduce these costs is through energy efficiency measures. However, they only address the increase in average electricity prices. To minimize price and emission peaks caused by high fluctuations, participants in the spot market must employ energy flexibility measures (EFM).

VDI Guideline 5207 [7] recommends different EFM depending on the request time and mainly addresses the topics of intervening the process or storing energy. For this publication, we will focus on the second approach, assuming that companies do not want to modify their current processes initially, and thus, the energy demand is considered to be given. However, the purchase of an energy storage unit alone is insufficient. Instead, the complete energy supply system needs to be capable of energy-flexible operation. This applies in particular to the expansion of the system and control technology.

The last step in implementing EFM involves defining Energy-Flexible Operating Strategies (EFOS). Specifically, for the category “store energy”, EFOS determines the timing for loading and unloading energy storage units. The decision of when to load and unload is based on criteria such as the target value, which could be the minimization of operating costs or the minimization of CO2 emissions associated with energy provision, and the corresponding cost function. When prices for electricity or carbon intensities are low, it is advisable to load storage units; however, when costs are high, it is generally best to unload them.

Why is a forecast necessary to identify loading intervals?

While it may be contended that current values in combination with recent values would be adequate to make a decision, this presumes that the systems are constantly operational and that there is enough power to charge the energy storage units. In reality, however, the systems are usually inert, or the actual systems temporarily require so much power that efficient loading is not possible. In addition, many large consumers obtain their prices directly from the spot market and have to submit their bids the day before. Consequently, it is mandatory to identify a trend for prices and emissions at an early stage and to develop matching EFOS.

This publication therefore introduces a forecasting tool specifically designed for industrial users and EFOS developers to address this challenge. The program operates on Python and loads necessary input data from selected APIs via the internet. The machine learning model employed in this program is trained with data obtained from the German energy market, but it could theoretically be applied to other countries as well (as long as the input data are publicly available).

Following an overview of the essential modelling basics, the third section of this publication details the method and tool structure. Finally, after validation, an exemplary use case is presented to demonstrate the use of the tool for the creation of EFOS.

2. FUNDAMENTALS

2.1 Existing approaches

Electricity price forecasting has become a key area of research in the energy sector. During the last decades thousands of papers on energy forecasting have been published making the progress in this field not easy to follow. [8, 9] This section gives a brief overview on the most common methods as well as those considered state-of-the-art.

Typically, the literature on energy price forecasting is grouped into five areas: *multi agent models* simulating the operation of interacting market agents, *fundamental methods* considering physical and economic factors, *reduced-form models* characterizing statistical properties of energy trade, *statistical models* comprising statistical techniques and econometric models, and *machine learning methods* being able to adapt to complex dynamic systems. Approaches combining techniques of two or more groups from this classification are so called *hybrid methods.* For forecasting day-ahead prices statistical models and machine learning methods have shown to give the best results. [10]

Common statistical methods are: autoregressive (AR) and autoregressive with exogenous inputs (ARX) models [11], threshold ARX (TARX) models [12], autoregressive integrated moving average (ARIMA) models [13, 14], double seasonal Holt-Winter (DSHW) models [15], semi/nonparametric models [11, 16], dynamic regression (DR) and transfer function (TF) models [17] or generalized autoregressive conditional heteroscedasticity (GARCH) based models [18–20]. Common hybrid versions of these models are wavelet-based models [14, 21, 22]. [23]

Usually, statistical models are linear forecasters being able to handle data with a low frequency e. g. weekly patterns, with success [23]. Another advantage of these models is their interpretability. Being criticized for their limited ability of modelling nonlinear behavior of electricity prices, in practical applications their performance is alike to non-linear alternatives [10]. The Lasso Estimated Autoregressive (LEAR) model [24] is considered as state-of-the-art among statistical methods and is argued to be the most accurate linear model by [9]. LEAR is a parameter-rich ARX structure with a fully automated feature selection procedure. The optimal set of features is selected using LASSO [25], based on L1-regularization.

To cover the need for forecasters being able to predict the nonlinear behavior of hourly prices, which might be too complicated to predict for many statistical models, machine learning methods have been proposed. The most commonly used ones are artificial neural networks [26–30], radial basis function networks [30], support vector regressors [31], and fuzzy networks [32]. Especially Deep Learning methods are characterized by the most rapid development together with hybrid methods [9]. In the study of [23] four Deep Learning models are proposed (a deep neural network model, a long-short term memory (LSTM) model, a gated recurrent unit model and a convolutional neural network model) and compared against a total of 23 different models, including 15 statistical methods, 7 machine learning models and a commercial software using a whole year of data for the day-ahead market in Belgium. The results of the study show that the deep neural network, LSTM, and gated recurrent unit models are statistically significantly better than all the considered models. The deep neural network model in particular outperforms any of the compared models. The automated and relatively simple Deep Learning method with two hidden layers using Bayesian optimization for hyperparameter and feature optimization, is therefore considered the second state-of-the-art model for energy price forecasting by [9]. [23] also shows a clear division between statistical and machine learning methods. Except for the LEAR model the machine learning models perform statistically significantly better than the statistical methods. Regarding hybrid models according to [9] it is impossible to find out which model is the best. This is because most of the hybrid methods have not been compared to each other nor to the state-of-the-art methods. In addition, the individual effect of each hybrid component is not analyzed.

In contrast to the rapid development and research activities in the field of energy price forecasting there are only few works found in the literature discussing short-term forecasting of CO_2 intensities. Since short-term CO_2 intensity forecasting on an hourly basis generally faces the same requirements and challenges as energy price forecasting as a consequence the same methods and models can be applied for both problems.

A common issue especially of models for energy price forecasting in the literature is the use of unique datasets with limited access for other researchers. In addition, many new methods are not compared with well-established or state-of-the-art models. This makes comparisons and analyses very complicated, if possible at all. [8, 9] Regarding the energy crisis of 2022 with significantly higher energy prices and volatility of renewable energy sources these issues are reinforced and could even challenge the current state-of-the-art models.

2.2 Extreme Gradient Boosting

The model for energy price and CO_2 intensity forecasting used in the proposed tool in this paper is XGB using the XGBoost library [33]. XGBoost stands for *Extreme Gradient Boosting* and is a scalable machine learning system for gradient tree boosting [34], also known as gradient boosting machine or gradient boosted regression tree. XGBoost is used for supervised learning. While the most frequent approach is to build only one single strong predictive model XGBoost follows the ensemble approach. It combines a large number of relatively weak and simple models, i. e. decision tree ensembles consisting of a set of classification and regression trees (CART), to achieve a stronger ensemble prediction. [35, 36] Other than most examples for

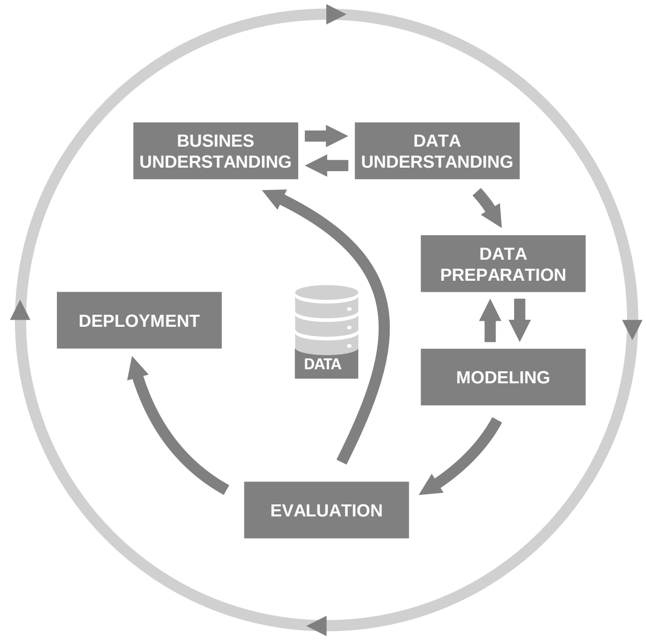

Fig. 2. Phases of the CRISP-DM Process Model for Data Mining. Based on [8]

ensemble techniques like random forests, which rely on simply averaging the models in the ensemble, boosting methods are based on a different strategy. The new weak decision trees are added to the ensemble sequentially at each particular iteration considering the error of the whole ensemble learnt so far by minimizing the error of the previous tree. The goal is to build new decision trees with a maximal correlation with the negative gradient of the loss function of the whole tree. [36] A regularized learning objective that penalizes the complexity of each decision tree tends to add simple and predictive decision trees. Together with the technique of shrinkage which reduces the influence of individual decision trees with smooth final learned weights and the technique of column subsampling this prevents overfitting. [33] Unlike artificial neural networks such as the LSTM, which is also well suited to predicting time series, there is no need to normalize the data before training. Coupled with efficient parallelization, XGBoost delivers excellent results at low implementation cost, making its scalability one of the most important factors behind its success. [33, 37]

3. METHOD AND IMPLEMENTATION

3.1 CRISP-DM

CRISP-DM (Cross-Industry Standard Process for Data Mining) is a proven and widely used project management model for data mining. Designed to provide a structured and repeatable approach to data mining projects, it consists of six main phases that are followed sequentially, but also allow for iterative feedback between phases. CRISP-DM helped us to manage the complexity of the issue and ensured the success of the project through a structured approach.

The first phase of CRSIP-DM [38] (see Fig. 2) is the *BUSINESS UNDERSTANDING*, where the project goals and requirements are discussed and translated into a data mining problem. One of the main problems is the increasing volatility in exchange-based electricity price trading in recent years, which made it necessary to search for a way to use publicly available data to create an AI model that was superior to traditional methods. The second phase is *DATA UNDERSTANDING* and includes the initial data acquisition, actions to become familiar with the data, identify data quality issues and gain initial insights into the data. In this phase, we took a closer look at freely available data from the European Network of Transmission System Operators for Electricity (ENTSO-E) [39] and statistically evaluated trends over the last few years. In addition, the graphical presentation of the data has provided a better understanding of the complex interdependencies within electricity price trading. *BUSINESS* and *DATA UNDERSTANDING* are two phases that are closely linked and should be seen as an iterative process. The next Phase of the process is the *DATA PREPARATION*. It covers all actions to construct the final dataset from the previous raw data. Here we looked for a suitable method to transform the raw data into relevant features. In the fourth step, the phase of *MODELING*, various modeling techniques are chosen to optimize the parameters of the model.

In this phase, we looked at different machine learning approaches and evaluated their advantages and disadvantages in relation to the problem. We decided to use a gradient boosting approach due to its superior performance, ease of implementation and moderate training effort. Like the first two steps, Data Preparation and Modeling depend on each other and form an iterative process. The second last stage is the *EVALUATION* of the computed models to select the model which is best suited to the business objectives. Here, the model underwent assessment through cross-validation, while a practical example was used to evaluate the price and CO2 savings. It is often necessary to organize and present the acquired knowledge in a way that makes it accessible to the user. This is the purpose of the *DEPLOYMENT* phase of CRISP-DM. The requirements can range from writing a report to implementing the model into an existing process. Therefore, we have developed a tool that uses the trained model to calculate daily forecasts. [40]

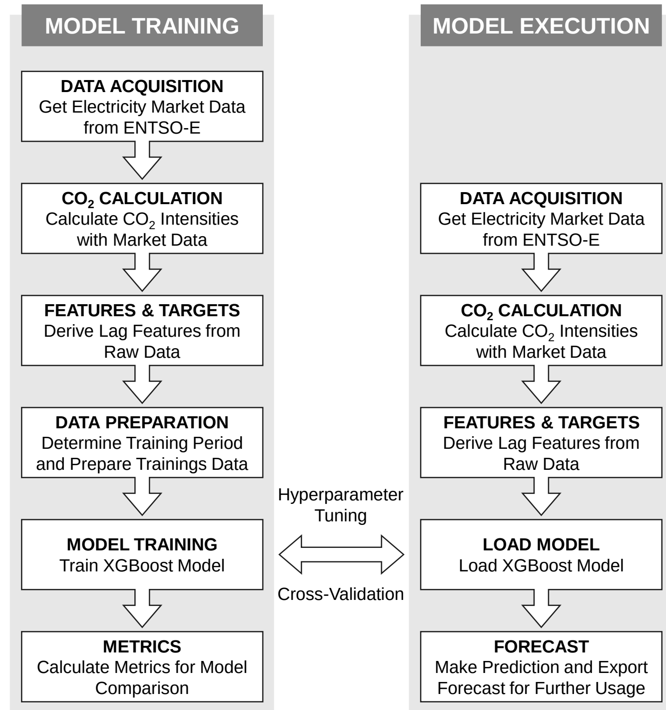

Fig. 3. Schematic illustration of the individual steps for model training and for model execution of the forecasting tool

3.2 Tool structure

The chosen model for forecasting energy prices and carbon intensities is XGBoost [33]. We trained our XGBoost model using only publicly available data from the ENTSO-E Transparency Platform. This platform provides a centralized hub for real-time and historical information related to electricity transmission across Europe. By using the ENTSO-E API, we can access a wide range of data, enabling them to perform comprehensive analyses, gain insights into the European energy market and build forecasting models.

As raw data we use the day-ahead price, the load forecast and the renewable energy forecast over a period from 2020 to 2023. Both forecasts are based on data such as weather models and historical energy production and consumption data. These forecasts play an important role in price formation by helping market participants to adjust their offers and avoid congestion. The 2023 data is used as a test dataset to evaluate the model.

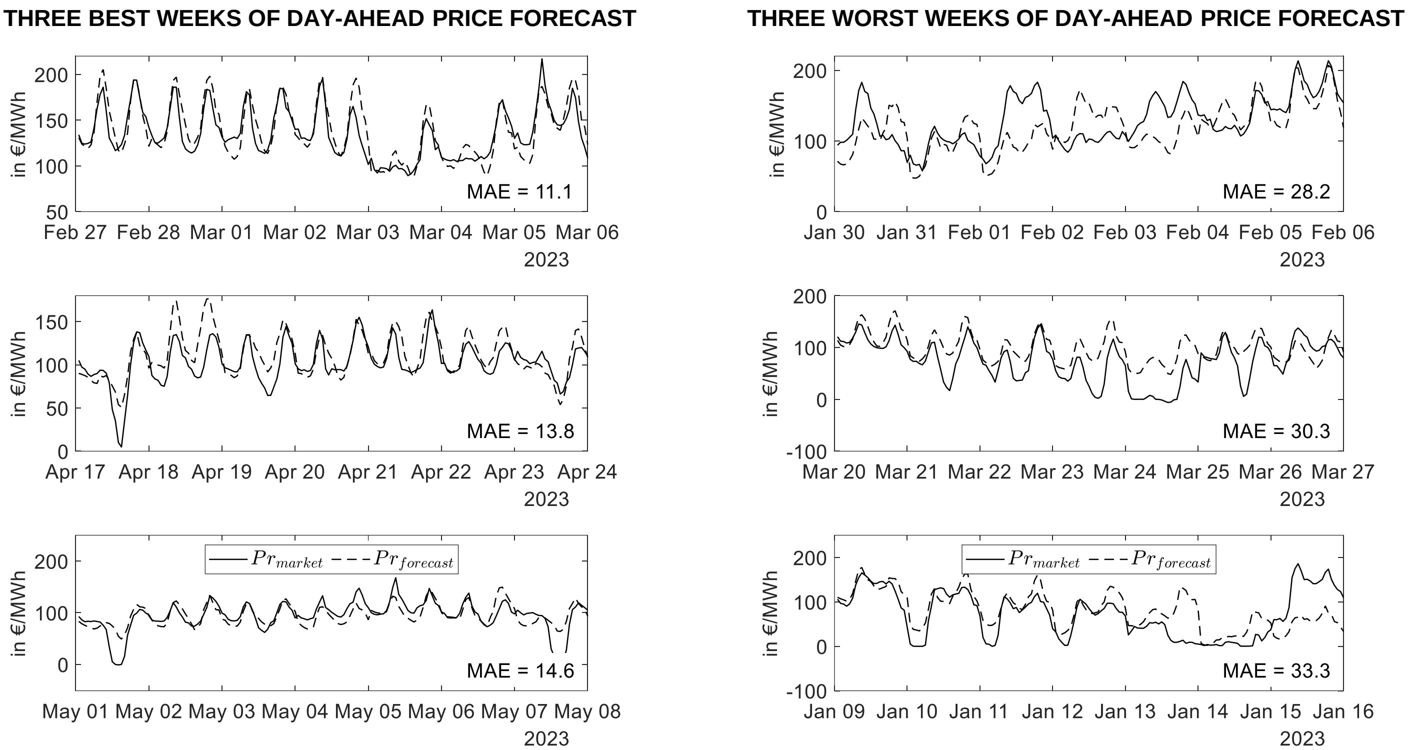

Fig. 4. Illustration of the electricity price forecast from the three best and from the three worst predicted weeks of the first half of 2023. The forecast data are compared with the respective market data.

The model is not trained on the raw data, but on lag features (meaning values of previous time steps in the time series), which are well suited for time series characteristics. In [9], a paper on best practices in energy price forecasting, Lago et al. describe a dataset of lag features that is also used in this project. Accordingly, we consider the historical day-ahead price of the previous three days and one week ago. The historical load and renewable energy forecasts are then lagged for the previous day and one week ago. In addition, the day of the week is added as an input feature. In total we get 241 features per day.

The target for the energy price forecasting model is the next 24 hours of price data after the day-ahead price. For the Carbon intensity forecasting model, we need to forecast the next 48 hours. The carbon intensity forecast is calculated with historical data of the actual generation per production type and its corresponding CO_2 emission factors for each production type. The CO_2 emission factors are provided by the open-source visualization of Electricity Maps [41].

A random grid search is used to optimize the number of estimators and the maximum depth of each decision tree. For cross-validation purposes, the training data is split into five parts with a time series split and twenty iterations are calculated for each split to find the best hyperparameters. The models are then saved, to use them later in the forecasting tool. A flow chart of the training process and execution of the forecasting tool are shown in Fig. 3.

The tool is structured in four steps. First, we load the latest energy data and generate our feature set. Since both models use the same feature set, this step only needs to be performed once. Second, we load the energy price and carbon intensity model. Next, we predict the energy price and the carbon intensity. The predicted energy price is then combined with the already available day-ahead price to obtain 48 hours of price information. Finally, the data is plotted and stored for later analysis.

4. EVALUATION AND INDUSTRIAL USE CASE

4.1 Validation

The forecasting model presented in Section 3.2 will be applied over an extended period in this section and evaluated for its predictive accuracy. To achieve this, the model is incrementally fed with historical data from the first half of 2023. In this simulation, similar to its real-world application, the model can only access data for the next day, obtained via the API, and data from recent past days. Using the XGBoost model, it computes the forecast for the subsequent two days. For electricity prices, only

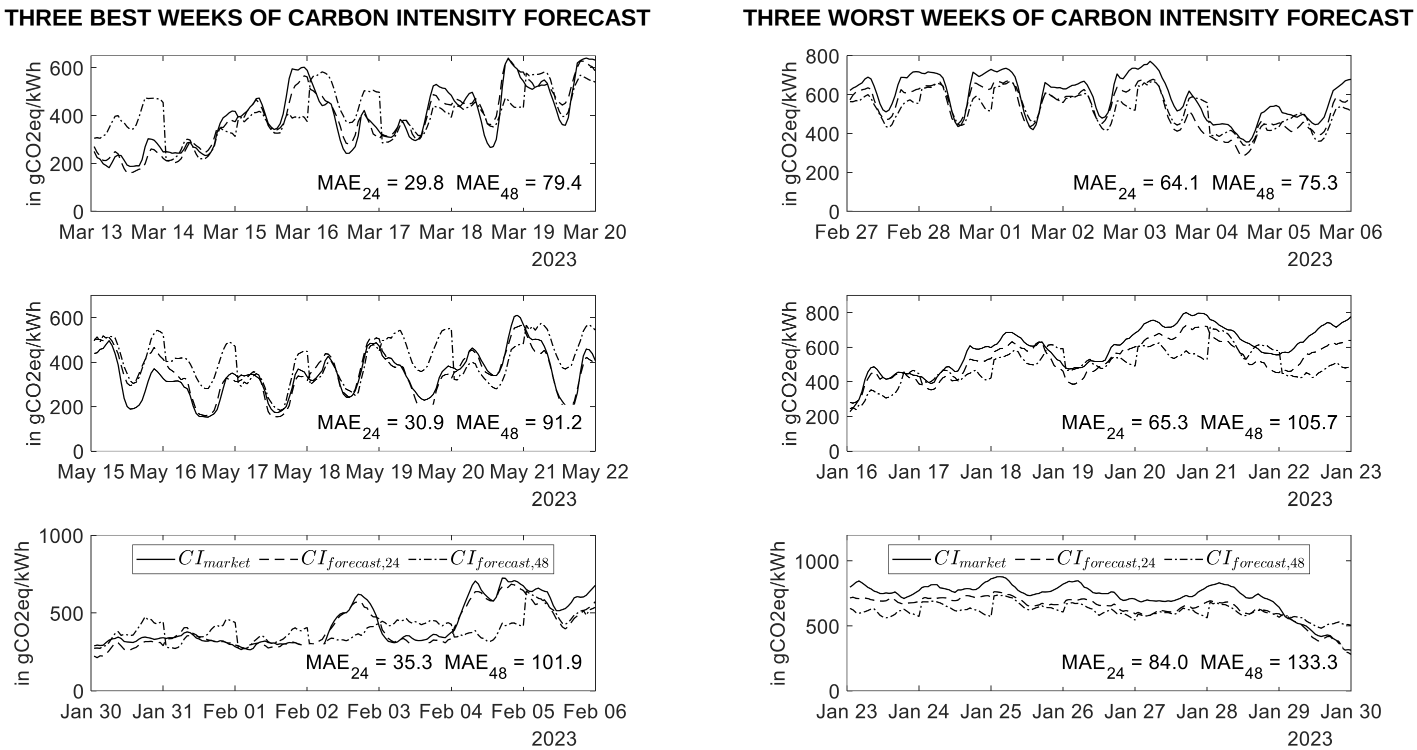

Fig. 5. Illustration of the carbon intensity forecast from the three best and from the three worst predicted weeks of the first half of 2023. The forecast data are compared with the respective market data.

the day after the next is predicted, as the next day's values are already provided by the Day-Ahead prices. The results of both the Day-Ahead electricity price forecast $Pr_{forecast}$ and Carbon intensity predictions $CI_{forecast}$ are compared against the actual market data Pr_{market} and CI_{market}. The MAE (Mean Absolute Error) is then calculated. Over the six-month period under review, the average MAE is 20.6 €/MWh for $Pr_{forecast}$ and 47.7 gCO2eq/kWh for the first day and 92.0 gCO2eq/kWh for the second day of $CI_{forecast}$.

To illustrate the temporal trends of market data and forecasted data, Fig. 4 displays the three weeks from the first half of 2023 that exhibited the highest alignment with the market data (lowest MAE) and the three weeks with the highest average deviations (highest MAE). Examining the three best weeks, the forecast closely matches the market data. Minor deviations only occur for outliers or significant deviations from the generally cyclical market behavior, with MAEs ranging from 11.1 €/MWh to 14.6 €/MWh.

For the three worst weeks, deviations are noticeably higher, with MAEs between 28.2 €/MWh and 33.3 €/MWh. However, when developing EFOS, not only are the amplitudes crucial, but the temporal overlay of local extremes is also vital. Ideally, the minima of the predicted data should align with the market data minima and vice versa for the maxima. In the worst-case scenario, the forecasted minima coincide with the market maxima, or the forecasted maxima match the market minima. In such cases, subsequent EFM would exacerbate volatile costs, rendering them counterproductive. As Fig. 4 indicates, even during the three worst weeks, the local extremes still align well, suggesting potential savings if EFM are correctly applied.

An analysis of the price extremes over the entire observation window for various tolerances yielded the following percentage overlaps for respective extremes:

- Without any tolerance: 39.4 %
- With ±1 hour tolerance: 78.4 %
- With ±2 hour tolerance: 87.2 %
- With ±3 hour tolerance: 92.0 %

In practice, depending on the inertia of the system under consideration, different tolerances become relevant. For the thermal energy systems discussed in this study, tolerances of ±2 hours are sufficiently accurate. The electricity price forecasts provided by the forecasting model thus offer a beneficial foundation for subsequent optimization models, with both amplitude and temporal occurrence of extreme values aligning closely.

Fig. 5, analogous to the results of $Pr_{forecast}$, displays the three best and worst weeks of $CI_{forecast}$. However, in contrast to Fig. 4, two forecasts are plotted: one for $t + 24h$ and another for $t + 48h$. The arrangement of weeks in Fig. 5 is based on the MAE_{24} results. Concerning the average carbon intensities, the prediction model achieves great results, with MAE_{24} ranging from 29.8 gCO_{2eq}/kWh to 84.0 gCO_{2eq}/kWh. For the $t + 48h$ forecast, values range between 79.4 gCO_{2eq}/kWh to 133.3 gCO_{2eq}/kWh. Even here, the impact of occasional higher amplitude errors on subsequent optimization processes is mitigated by the favorable temporal occurrences of the extreme values. These are as follows for the $CI_{forecast}$:

- Without any tolerance:
  29.7 % (24h); 21.8 % (48h)
- With ±1 hour tolerance:
  62.3 % (24h); 50.7 % (48h)
- With ±2 hour tolerance:
  79.2 % (24h); 68.5 % (48h)
- With ±3 hour tolerance:
  86.6 % (24h); 78.5 % (48h)

Again, the primary relevant tolerances are up to ±2 hours. Although the 48h forecast results remain sufficiently accurate for EFM decision-making, if possible, the more accurate 24h forecast values should be utilized.

4.2 Exemplary Use Case

This section illustrates the application of our forecasting model within an exemplary use case. The aim is to devise an EFOS, thereby reducing both the operating costs and CO_2 emissions of the system under consideration. The system under consideration is a decentralized cooling supply system for an air handling unit (AHU), consisting of a compression chiller, a thermal energy storage (TES) and a heat exchanger connected to the primary heat source: the AHU. While the predictive model remains central to this discourse, we will avoid a deep dive into the granular technicalities of the cooling supply system or the simulation model. Detailed discussions of the component functionalities and the simulation model are available in the referenced literature [42].

As previously outlined, our overall objective is to synchronize the energy demand of the consumers (here

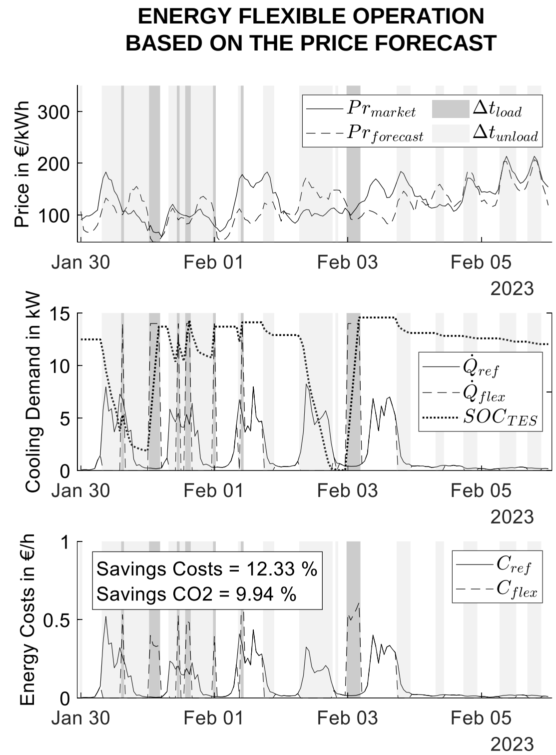

Fig. 6. Presentation of the calculation basis and the results of the exemplary use case for reference operation and for energy-flexible operation. Highlighting the loading and unloading phases.

the electrical power of the compression chiller) with temporally defined windows characterized by minimized electricity prices and/or carbon intensities, while maintaining the uninterrupted functionality of the system. Following the "energy storage" measure of [7], this requires the identification of promising intervals for both loading and unloading the TES. The forecasting model was used to predict daily electricity prices and carbon intensities for the following day throughout the first half of 2023. This forecast, combined with historical data from the previous day, was used to find profitable time windows for loading and unloading the TES.

The trajectories of both market Pr_{market} and forecast $Pr_{forecast}$ data are illustrated in the top segment of Fig. 6. As our optimization criterion for this use case is focused on minimizing electricity costs. carbon intensities, although calculated, are not included in this chart.

Using the simulation model and guided by the preliminary windows indicating the potential profitability of loading or unloading, we identified the actual loading Δt_{load} and unloading Δt_{unload} intervals. As Fig. 6 shows, there are intervals outside of Δt_{load} and Δt_{unload}. During these periods, the compression refrigeration unit operates in direct cooling mode, bypassing loading or unloading actions that aren't considered efficient - for example, when the TES is at full capacity and its conserved energy is more sensibly reserved for subsequent unloading phases. The second segment of Fig. 6 shows the cooling requirements of the reference scenario $\dot{Q}_{ref}$. $\dot{Q}_{flex}$ is spread across the Δt_{load} intervals, while the cooling required during Δt_{unload} is provided by the TES, as observed in the SOC trajectory.

Finally, the third segment of the figure compares the cost vectors of the benchmark scenario C_{ref} with the energy-flexible operation C_{flex}. Within the observation window from 30 January to 5 February 2023, the energy-flexible operation generates a cumulative cost saving of 12.33 % compared to the benchmark operation. At the same time, the associated CO2 savings are 9.94 %, highlighting the strong correlation between electricity prices and carbon intensities.

The time interval shown in Fig. 6 best represents the median savings for the first half of 2023. Importantly, the SOC begins and ends the interval with comparable values, ensuring an authentic representation of savings so that divergent storage states do not distort the results.

5. CONCLUSION AND OUTLOOK

In energy forecasting, the results of the model presented in this work are promising. Our model's ability to predict energy trends demonstrates its potential for wider real-world applications. Although there are some discrepancies between the model's predictions and actual market data, they remain sufficiently small, suggesting a good level of reliability. This consistent performance instills confidence that the forecasts can be valuable inputs when assessing EFM. Furthermore, our exemplary use case provides compelling evidence of the model's utility. Through its application, there's a distinct potential for significant reductions in both operational costs and CO_2 emissions associated with energy provision. The versatility of the model suggests that, depending on the specific context of its implementation, the savings identified could even be exceeded.

Looking ahead, the model can be seamlessly integrated into the control mechanisms of a real production facility. By combining this with a simulation model and applied operational optimization, there is an opportunity to analyze and validate the effectiveness of the model over long periods of time. A key focus will be to determine optimal intervals for iterating the training of the model, as shown in Fig. 3. This iterative approach ensures that the forecasting tool remains current and relevant. Finally, given the universal challenges and opportunities associated with energy management, adapting the model to handle international datasets seems a logical progression. This adaptation would pave the way for its use beyond German borders, making its insights and benefits available to a wider global audience.

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DECLARATION OF INTEREST STATEMENT

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. All authors read and approved the final manuscript.

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