Article

Day-Ahead Electricity Price Forecasting Using Gradient Boosting Models Decision Tree Models: A Case Study of the Croatian Market

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Abstract

Accurate day-ahead electricity price forecasting is essential for market participants to optimize bidding strategies and manage financial risks in increasingly volatile energy markets. This paper presents a comprehensive web-based system designed for day-ahead electricity price forecasting based on gradient boosting models, specifically applied to the Croatian market. The proposed approach integrates a multi-layered architecture that includes data ingestion from ENTSO-E and Open-Meteo, a robust backend for model selection, training and management, with an interactive frontend presentation layer. The performance of two state-of-the-art gradient boosting algorithms, XGBoost and LightGBM was evaluated using hourly DA market price data from 2022 to 2024 from Croatian electricity market. The results demonstrate that both models achieve similar accuracy for the year 2024. Monthly analysis reveals significant performance variations, with higher errors during periods of extreme volatility and price spikes, such as summer and late winter. The study highlights the importance of meteorological features and market fundamentals in capturing price dynamics.

Keywords: electricity price forecasting; day-ahead market; gradient boosting; XGBoost; LightGBM; Croatian energy market

1. Introduction

Accurate day-ahead electricity price forecasting (EPF) is of great importance in modern, liberalized energy markets. For different market participants, ranging from an energy producers and utility companies to a large industrial consumers and traders, precise DA price forecasts are critical for effective bidding strategies, managing financial risk, and optimizing operational planning [1,2]. However, with increasing share of RES and geopolitical tension affecting fossil fuel prices, the task of forecasting electricity prices has grown increasingly complex. The rising penetration of intermittent energy sources (IES) such as wind and solar power introduces significant volatility into the supply side, while the implementation of demand response (DR) programs adds to variability on consumption side [3,4]. These factors challenge the capabilities of traditional forecasting method and contribute to DA market price non-linearity, non-stationarity, and the frequent occurrence of extreme events like price spikes.

EPF methods, driven by advances in computational power and the increasing complexity of energy markets, have evolved significantly over the past two decades. The wide

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range of these approaches, reflecting a path from simple assumption-driven techniques to very adaptable data-driven frameworks, can be broadly classified into four main categories:

- **Statistical and Econometric Models:** This category represents the foundational approach to time series forecasting. In this approach models rely on mathematical equations and statistical properties of historical data to identify and extrapolate patterns. Several key models are commonly referred to in the literature such as Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Multiple Linear Regression (MLR) [1,5–7]. These approaches can also be part of more advanced techniques such as probabilistic forecasting, which are designed to produce a range of possible outcomes instead of just a single point value.
- **Classic Machine Learning Models:** include non-neural network algorithms capable of capturing more complex, non-linear relationships that traditional statistical models often miss. These models learn patterns directly from the data without being explicitly programmed with mathematical assumptions about the underlying data-generating process. Prominent examples found in the EPF literature include Support Vector Machines (SVM) and their regression variant (SVR), tree-based ensemble methods like Random Forests (RF), and instance-based algorithms such as K-Nearest Neighbors (KNN) [8,9].
- **Deep Learning and Neural Network Models:** Most prominent and rapidly advancing category, deep learning leverages multi-layered artificial neural networks (ANNs) to model highly complex, non-linear, and hierarchical patterns within large datasets. The architectures vary: Multilayer Perceptrons (MLPs) handle general tasks, while Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs) work better for sequential data. Newer architectures like MAMBA aim to handle long time series more efficiently. [2,10–12].
- **Hybrid and Ensemble Models:** This category is defined by multi-stage frameworks that combine techniques from the other categories to leverage their complementary strengths and mitigate individual weaknesses. Hybrid models combine techniques from multiple categories in a pipeline. A typical setup might use a signal decomposition method (like Variational Mode Decomposition or Ensemble Empirical Mode Decomposition) to pre-process the data, then feed the results into a forecasting model such as an LSTM network [13–15]. Another approach is ensembling — running several different models and aggregating their predictions. Either way, the idea is that combining methods often achieves superior accuracy and robustness compared to any single constituent model.

The proposed research contributes to the field by implementing a practical, web-based forecasting system that utilizes state-of-the-art gradient boosting models tailored for the Croatian electricity market. The paper is structured as follows: Section 2 covers the system architecture, forecasting methods, data, and evaluation metrics. Section 3 presents results and compares model performance. Section 4 summarizes findings and discusses future directions.

2. Methodology

This section describes the architecture of the proposed web-based system for day-ahead electricity price forecasting. The overall architecture is illustrated in Fig. 1.

The proposed architecture has five main layers: presentation layer, backend services layer, intelligence layer, persistence layer, and data ingestion layer:

- **Presentation layer**: is implemented as a React-based web dashboard, which provides users with interactive access to historical electricity price data and day-ahead forecast

results. The frontend communicates with the backend exclusively through RESTful HTTP/JSON interfaces, ensuring loose coupling between the user interface and the underlying system logic.
- **Backend services layer**:A REST API gateway that handles authentication, data retrieval, forecast requests, and model training triggers. It validates requests, checks permissions, and routes them to the appropriate components.
- **Intelligence layer**: contains the machine learning models used for day-ahead electricity price forecasting. In the current implementation, XGBoost and LightGBM gradient boosting models are employed due to their robustness and predictive performance on structured time-series data. The layer supports both inference and retraining, so models can be updated as new market and meteorological data become available.
- **Persistence layer**: consists of two complementary data storage systems: a relational SQL database for user accounts and configuration, and InfluxDB (a time-series database) for electricity prices, weather data, and forecast outputs.
- **Data Ingestion and Scheduling Layer**: automated data ingestion is handled by a task scheduling component that periodically retrieves data from external sources. Market data are obtained from the ENTSO-E platform, while meteorological data are sourced from the Open-Meteo API. The scheduler ensures periodically data acquisition, preprocessing, and storage in the time-series database, providing necessary inputs for day-ahead forecasting.

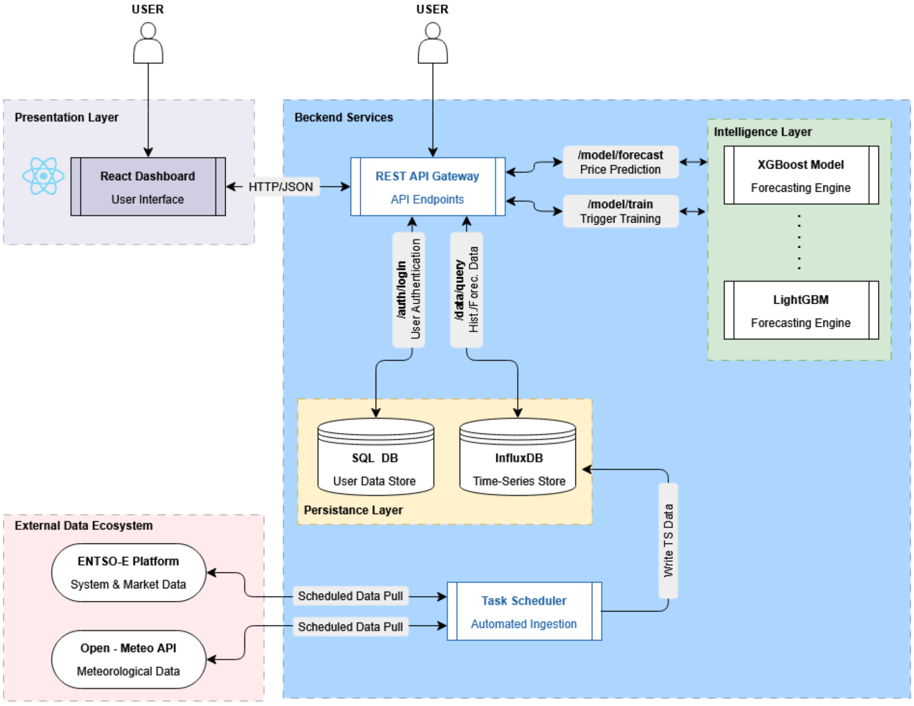
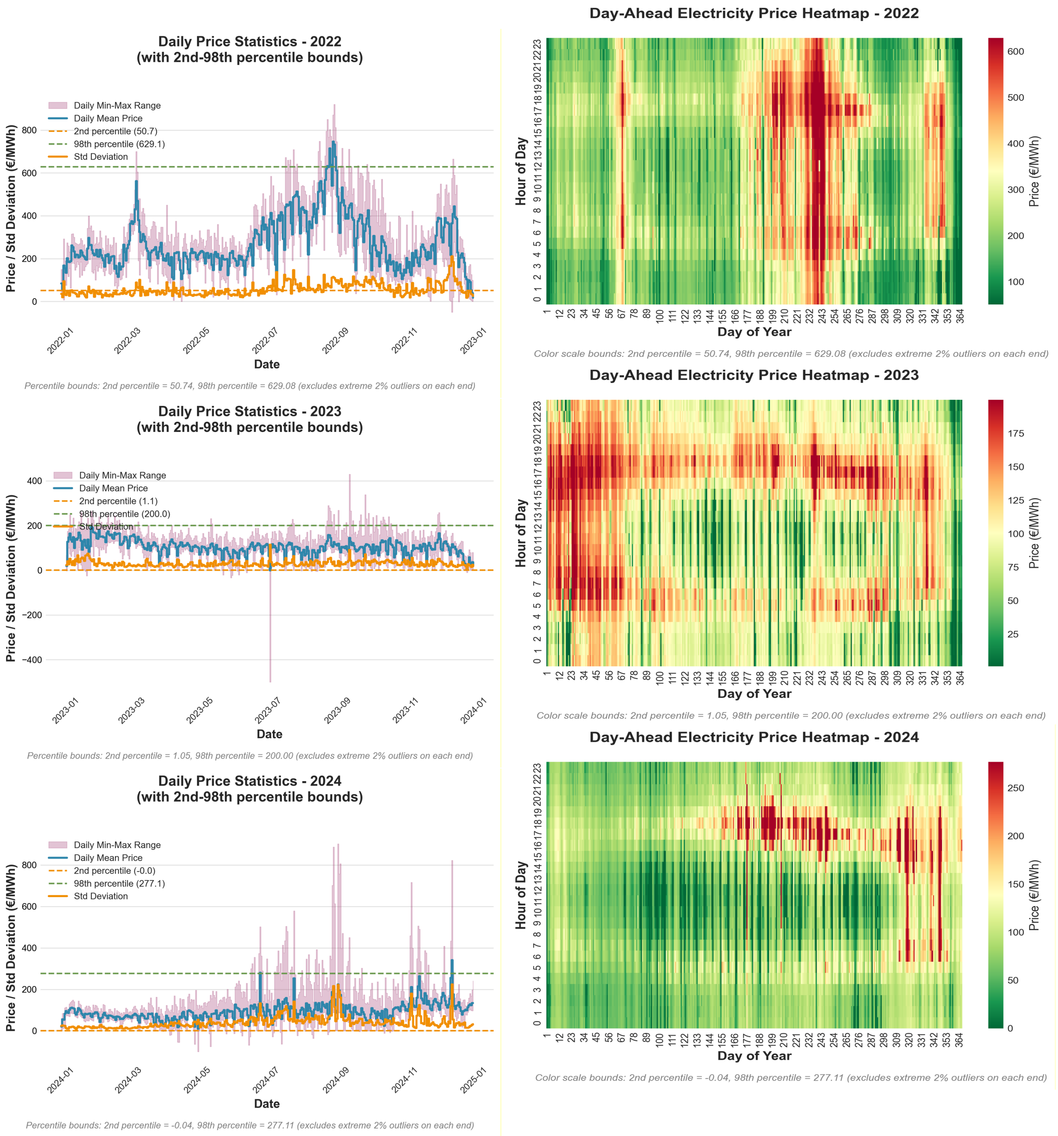


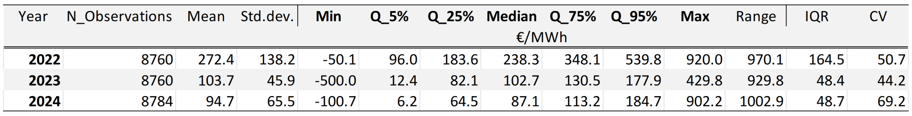
Figure 1. Electricity price prediction system architecture.

2.1. Data description

The data used for model training and validation represents hourly wholesale electricity prices from Croatian DA electricity market. The data used in the analysis is obtained from the ENTSO-E Transparency Platform (results of CROPEX DA market clearing). The dataset covers the period from 1 January 2022 to 31 December 2024. In addition to DA market price data, selected dataset also includes meteorological parameters that influence electricity demand and supply patterns. Historical weather observations as well as weather forecast data for the same period are sourced from the Open-Meteo database. This lets the model account for weather's effect on electricity demand and supply.

From the Figure 2 we can see that the prices of electricity in Croatia are very volatile, with sudden and sometimes sharp increases occurring especially when the demand is high and the system is heavily loaded, as well in conditions with low system load and high RES production. In addition to this, the data show typical seasonal patterns, with the higher prices in the winter and summer months, while the weekends normally bring lower average prices when compared to the weekdays. The presence of outliers, the changes in volatility over time, and the strong seasonality of both price and weather variables pose great difficulties for accurate electricity price forecasting.





Year	N_Observations	Mean	Std.dev.	Min	Q_5%	Q_25%	Median	Q_75%	Q_95%	Max	Range	IQR	CV
							€/MWh						
2022	8760	272.4	138.2	-50.1	96.0	183.6	238.3	348.1	539.8	920.0	970.1	164.5	50.7
2023	8760	103.7	45.9	-500.0	12.4	82.1	102.7	130.5	177.9	429.8	929.8	48.4	44.2
2024	8784	94.7	65.5	-100.7	6.2	64.5	87.1	113.2	184.7	902.2	1002.9	48.7	69.2

Figure 2. DA ahead electricity prices from 2022 to 2024 in Croatian electricity market.

Figure 2 shows hourly heatmap as well as daily average prices with min-max price range for the observed period. From the figure and table below, we can see high prices during summer 2022 and summer/autumn 2024. The sharp rise in electricity prices in Summer 2022 was primarily a result of several negative factors occurring after a pandemic, a war in Ukraine affecting gas prices, less hydro/nuclear supply from droughts/plant maintenance, while the Summer/Autumn 2024 period was defined by high prices that occurred mainly due to the persistence of high gas/carbon prices, grid constraints especially in south-east Europe, and increased electricty demand for cooling. This periods also shows high volatility with frequent price spikes. On the other hand 2023 was marked by lower and more stable prices due to milder weather conditions, increased renewable generation, diversification of gas supply in EU and sufficient gas reserves.

2.2. Feature selection

Effective feature selection is a important part of EPF because electricity prices are highly volatile and non-linear time series which are influenced by a large number of different variables [16,17]. Given this, by removing irrelevant or highly corelated features, forecasting models can better learn input/output mappings, improving in that way prediction accuracy and reducing computational complexity[9,16].

Feature selection methodologies can be categorised into three primary types:

- **Filter Methods**: represent preprocessing step which is independent from the learning algorithm. They use specific criteria to determine the information value of feature data inputs. Correlation Analysis (CA) measures linear relationships while Mutual Information (MI) and Interaction Gain (IG) capture non-linear ones. Filtering methods and indicators can determine feature value from the aspect of relevancy (how much information they provide about the target), redundancy (how much common information they share with other features), and interaction/synergy (how much additional information they provide when used together)[16].
- **Wrapper Methods**: search through subsets of features and use the estimated accuracy of a specific learning algorithm as the measure of goodness. This approach tends to be more accurate but slow on large datasets. Examples include Genetic Algorithms, Firefly Algorithm, and Stepwise Regression.[15,16].
- **Hybrid Approaches**: represent the combination of filter and wrapper techniques that are used in combination to exploit the strengths of both approaches. A typical implemetnation consits of first applying a filter methods to narrow the feature set based on relevancy, redundancy, and synergy, and then applying a wrapper methods to minimise validation error[16].

Other techniques used for dimensionality reduction include Principal Component Analysis (PCA) and Grey Correlation Analysis (GCA), which aim to reduce the size of the input set while preserving essential information[8,16].

The main features that are typically used in EPF usually consist of a mix of endogenous (internal) and exogenous (external) variables:

- **Lagged and Window Data**: recent historical electricity prices are usually the most critical predictors of future prices[7]. Typical features derived from historical DA market prices data that are used in EPF include lagged prices from the previous hour, the same hour on the previous day, or the same hour in the previous week (e.g., lags of 1, 24, and 168 hours)[7,10,11]. In addition to these features, the window features usually include average, min/max values, standard deviations etc., over recent historical data spanning usually across 24 hours or larger time intervals. Similary, lagged historical electrity power demand values are also often used due to the strong correlation between load patterns and price fluctuations[13,18,19].
- **Temporal and Calendar Indicators**: are used to derive features that capture the seasonal and cyclical nature of electricity markets[17,20]. They include the hour of the day, day of the week, day of the month, month of the year, as well as binary indicators for holidays or weekends[7,10,11,13,18].

- **Weather Variables**: are also used as an important feature given that they significantly impact both supply and demand. The most important variable is temperature given its influence on energy needs for heating and cooling. Other often used relevant features include wind speed (critical for wind power generation), solar radiation, and precipitation[7,13,17,21].
- **Generation Data and Market Fundamentals**: this set of variables usually include the generation mix (e.g., wind, solar, fossil, nuclear, and hydro production levels), available generation capacity, and forecasted outages[1,8,13,16].
- **Energy Commodity Prices**: include features derived from natural gas prices trends, coal, crude oil, CO2 emmisions. These features are often used in medium- and long-term electricty price trend predictions[1,7,13,15,22].
- **Spike Indicators** : are often used in more advanced models, where special predictors are used to detect price spikes and extreme fluctuations caused by short-term supply-demand imbalances. To improve regression accuracy, electricty prices in such prediction models are often categorised as either normal or extreme [8].

2.3. Error measures

Different statistical metrics are used to quantify the accuracy of EPF models and to measure the error between predicted and actual market prices [18,21]. These indicators can be categorised into three main categories: point forecast metrics, uncertainty measures, and probabilistic evaluation criteria [8,17].

Point forecasts are used to predict a single value for each time step, and in this types of forecasts, the model error is usually evaluted based on following indicators:

- **Mean Absolute Error (MAE)**: represents the average magnitude of errors in a set of predictions, without considering error direction [8,13]. This indicator is highly valued for its interpretability and is frequently used to assess general model performance [9,10].
- **Root Mean Square Error (RMSE)**: calculates the square root of the average of squared differences between prediction and true value [8,19]. Because it squares errors before averaging, larger errors are penalized more heavily which is useful for catching outliers or price spikes. [2,8]
- **Mean Squared Error (MSE)**: is often used as the loss function during the algorithm training phase and it provides the basis for optimising model parameters[3,22,22]. MSE is defined as average squared error between predictions and true values.
- **Mean Absolute Percentage Error (MAPE)**: expresses the error as a percentage of the actual price [11,13]. While widely used, it can become unstable or skewed when actual electricity prices are near zero, which is a nowdays common situation in electricity markets with high renewable penetration [4,5].
- **Symmetric Mean Absolute Percentage Error (SMAPE)**: To address the limitations of MAPE in volatile markets, SMAPE provides a scale-independent measure that avoids MAPE's instability near zero prices by using a scale-independent formula [3,18].
- **Coefficient of Determination (R^2)**: indicates the degree of the variance in electricity prices that is predictable from the independent variables. It provides a measure of how good the model captures the underlying data patterns[3,19].

Table 1. Error metrics formulas.

$\mathrm{MAE}(y,\hat{y}) = \frac{\sum_{i=0}^{N-1} \lvert y_i - \hat{y}_i \rvert}{N}$	(1)	$\mathrm{RMSE}(y,\hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1} (y_i - \hat{y}_i)^2}{N}}$	(2)
$\mathrm{MSE}(y,\hat{y}) = \frac{\sum_{i=0}^{N-1} (y_i - \hat{y}_i)^2}{N}$	(3)	$\mathrm{MAPE}(y,\hat{y}) = \frac{100}{N} \sum_{i=0}^{N-1} \frac{\lvert y_i - \hat{y}_i \rvert}{\lvert y_i \rvert}$	(4)
$\mathrm{SMAPE}(y,\hat{y}) = \frac{100}{N} \sum_{i=0}^{N-1} \frac{2 * \lvert y_i - \hat{y}_i \rvert}{\lvert y \rvert + \lvert \hat{y} \rvert}$	(5)	$R2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}$	(6)

3. Results

The feature set includes historical prices, temporal indicators, weather variables, generation data, and market fundamentals — a mix of historical and forecasted, endogenous and exogenous inputs. Hyperparameters were tuned via grid search with cross-validation. The base models use only the top 30 features ranked by importance. Both models derive importance from tree splits and not model coefficients. Common measures are split frequency (how often a feature splits nodes) and gain (loss reduction from those splits). In forecast model based on XGBoost regressor gain is computed using second-order gradient statistics (gradients and Hessians) while LightGBM uses a similar loss-reduction approach but with histogram-based splitting and leaf-wise growth, which can produce different rankings.

The performance of the XGBoost and LightGBM models was evaluated for the year 2024. Table 2 summarizes the overall error metrics for both models. Both algorithms demonstrate comparable performance, with LightGBM showing a slight advantage in terms of R^2 (0.60) and RMSE (41.42), while XGBoost achieved a marginally lower MAE (24.62). These results indicate that both gradient boosting techniques are capable of capturing a significant portion of the price volatility in the Croatian market.

Figure 3 compares actual and forecasted DA electricity prices for 2024. Both models track overall price trends well, including daily and weekly cycles. However, challenges remain in accurately predicting extreme price spikes, which are common in electricity markets due to sudden supply-demand imbalances or unexpected weather events. Both models tend to underpredict these spikes, which drives up errors during those periods.

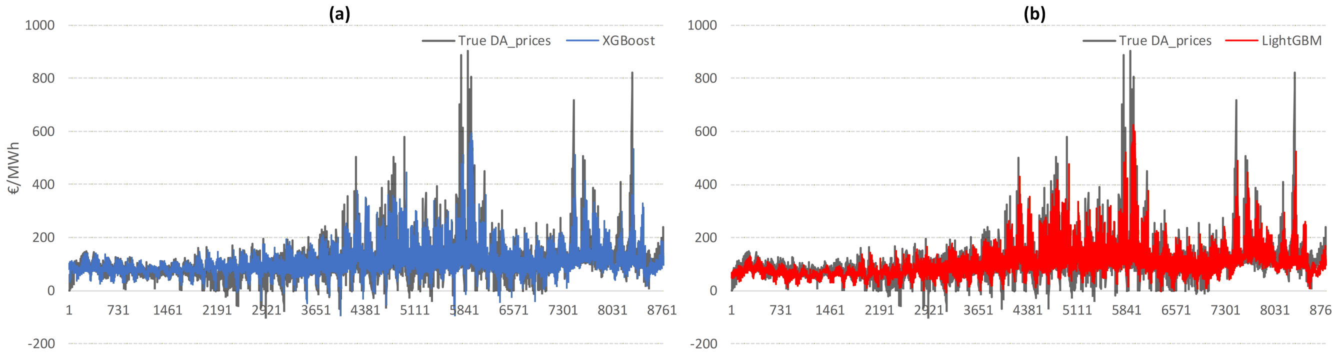


Figure 3. Actual vs forecast DA electricity prices for 2024 in Croatian electricity market.

A more detailed monthly analysis, presented in Table 3, reveals significant seasonal variations in forecasting accuracy. The models performed best during the spring and autumn months (e.g., October with R^2 up to 0.66), where price volatility was relatively lower. Conversely, the highest errors were observed in December, with MAE values near 40 and RMSE exceeding 60. This can be attributed to the increased frequency of price spikes and extreme weather events during the winter season, which are inherently more difficult to predict.

Table 2. Error metrics table for year 2024 for XGBoost & LightGBM model.

	MAE	RMSE	R2
XGBoost	24.62	41.84	0.59
LightGBM	25.20	41.42	0.60

Table 3. Error metrics monthly table data for year 2024 for XGBoost & LightGBM model.

Month	**XGBoost**			**LightGBM**		
	MAE	***RMSE***	***R2***	***MAE***	***RMSE***	***R2***
1	15.92	22.55	0.23	16.58	20.48	0.37
2	12.56	16.54	0.17	13.36	16.52	0.17
3	15.05	21.19	0.33	16.98	21.13	0.33
4	27.50	35.88	0.15	21.83	28.34	0.47
5	17.35	25.50	0.60	19.94	27.03	0.55
6	28.82	50.47	0.49	31.27	51.63	0.46
7	35.13	54.97	0.54	36.62	55.92	0.52
8	26.60	49.54	0.63	27.63	49.39	0.63
9	27.52	51.49	0.64	26.82	51.61	0.64
10	20.62	27.12	0.66	21.60	28.44	0.63
11	28.36	49.09	0.55	29.42	49.11	0.55
12	39.74	63.15	0.28	39.81	61.34	0.33

The comparison between XGBoost and LightGBM suggests both models perform similarly. Both models might improve with better feature engineering or additional market data — though some relevant inputs aren't available before the Croatian DA market closes.Also moving from point forecasts to probabilistic intervals would provide market participants with a better understanding of uncertainty, which is crucial for risk management.

4. Conclusions

This paper presented a web-based system for DA EPF in the Croatian market. By integrating automated data ingestion, a robust backend, and state-of-the-art gradient boosting models, the architecture provides a practical tool for energy market participants. Comparison between XGBoost and LightGBM models for the year 2024 showed that both algorithms are capable of achieving reasonable accuracy, with R^2 values around 0.60. However, significant performance variations across different months indicate the challenges related to market volatility and seasonal price spikes.

The study confirms that gradient boosting works well for this task, particularly with careful feature engineering. The future work will focus on enhancing the system's intelligence layer by incorporating deep learning models and probabilistic forecasting methods. Additionally, expanding the feature set to include more granular market fundamental data will be explored to further improve the robustness and reliability of the forecasts.

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supervision and funding acquisition, D.J. (Damir Jakus). All authors have read and agreed to the published version of the manuscript.

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