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ARTICLE

Day-Ahead Electricity Price Forecasting Using the XGBoost Algorithm: An Application to the Turkish Electricity Market

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ABSTRACT: Accurate short-term electricity price forecasts are essential for market participants to optimize bidding strategies, hedge risk and plan generation schedules. By leveraging advanced data analytics and machine learning methods, accurate and reliable price forecasts can be achieved. This study forecasts day-ahead prices in Türkiye's electricity market using eXtreme Gradient Boosting (XGBoost). We benchmark XGBoost against four alternatives—Support Vector Machines (SVM), Long Short-Term Memory (LSTM), Random Forest (RF), and Gradient Boosting (GBM)—using 8760 hourly observations from 2023 provided by Energy Exchange Istanbul (EXIST). All models were trained on an identical chronological 80/20 train–test split, with hyperparameters tuned via 5-fold cross-validation on the training set. XGBoost achieved the best performance (Mean Absolute Error (MAE) = 144.8 TRY/MWh, Root Mean Square Error (RMSE) = 201.8 TRY/MWh, coefficient of determination (R^2) = 0.923) while training in 94 s. To enhance interpretability and identify key drivers, we employed Shapley Additive Explanations (SHAP), which highlighted a strong association between higher prices and increased natural-gas-based generation. The results provide a clear performance benchmark and practical guidance for selecting forecasting approaches in day-ahead electricity markets.

KEYWORDS: Day-ahead electricity price forecasting; machine learning; XGBoost; SHAP

1 Introduction

Electricity price forecasting is a critical component of competitive power markets. Accurate forecasts allow generators, retailers, and consumers to optimize bidding strategies, hedge against price volatility, and support grid stability. In the Turkish electricity market, rapid demand growth and the increasing penetration of renewable energy have amplified price fluctuations and uncertainty. For example, the average day-ahead market price surged from approximately 300 TL/MWh in early 2021 to peaks exceeding 1500 TL/MWh in 2022, driven by supply-demand imbalances and external shocks (Energy Exchange Istanbul, 2022). Historically, short-term electricity price forecasting has relied on traditional statistical methods such as autoregressive integrated moving average (ARIMA) and other time-series models. These approaches are effective for capturing linear patterns, seasonality, and trends but often fall short in modeling the highly nonlinear and stochastic dynamics of electricity markets [1,2]. To address these limitations, researchers have increasingly adopted machine learning (ML) and artificial intelligence (AI) techniques, which offer greater flexibility in capturing complex relationships in price formation [3].

In recent years, artificial intelligence and machine learning-based approaches have been increasingly employed in energy market analysis. These methods offer higher forecasting accuracy due to their ability to extract complex patterns from large datasets. In particular, tree-based ensemble learning algorithms are favored for their ability to capture nonlinear relationships in data. Support Vector Machines (SVM), Random Forest (RF), Long Short-Term Memory (LSTM), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (XGBoost) have gained prominence in electricity price forecasting due to their capabilities in modeling nonlinear and complex temporal dependencies. SVM effectively captures non-linear relationships using kernel functions [4], while Random Forest (RF) leverages ensemble learning by combining many decision trees to model nonlinear relationships and excels at high-dimensional problems particularly when the number of predictors is large relative to observations [5]. LSTM networks, equipped with explicit memory cells and gating mechanisms, efficiently manage information flow to capture long-term sequential dependencies and mitigate the vanishing gradient issue [6]. Gradient Boosting Machines (GBM) and especially XGBoost as introduced by Chen and Guestrin [7] are efficient, regularized, scalable tree-boosting systems widely adopted in forecasting.

Despite significant advances in electricity price forecasting methods, gaps persist in the literature due to insufficient benchmarking across diverse models and techniques using consistent datasets and evaluation metrics, particularly within unique market contexts like Turkey's electricity market. Many studies often focus on single or hybrid models without comprehensive comparative analyses against alternative methods. To address these issues, this study provides a rigorous comparative analysis of five forecasting models SVM, LSTM, RF, GBM and XGBoost using hourly Turkish day-ahead price data from 2023. Additionally, SHAP (Shapley Additive Explanations) analysis is employed to enhance model interpretability by identifying the importance of input variables.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on electricity price forecasting, as well as prior studies on the Turkish electricity market. Section 3 describes the data, methodology, and forecasting models employed in the study, including details on hyperparameter optimization and performance evaluation metrics. Section 4 presents the experimental results and comparative analysis of the forecasting models, including graphical and SHAP-based interpretations. Finally, Section 5 concludes the study by summarizing key findings and offering recommendations for future research.

2 Literature Review

Electricity price forecasting has become an increasingly strategic area of research in energy markets due to rising volatility, market liberalization, and technological transformation. Among energy commodities, oil, natural gas, and electricity markets are among the most extensively studied in terms of price prediction. In electricity markets, the inability to store the product necessitates a real-time balance between supply and demand. These markets, characterized by dynamic and instant consumption, often experience price fluctuations, which emphasizes the importance of reliable and accurate forecasting models [1]. Factors such as increasing competition, infrastructure limitations, smart grid integration, and the increasing utilization of renewable energy sources have further intensified the need for effective load and price forecasting for system planning and operation [8]. Electricity price forecasts are generally classified into short-, medium-, and long-term categories depending on the planning horizon [9]. Electricity trading is conducted through Day-Ahead and Intra-Day Markets, in which both statistical and AI-based forecasting methods are employed [10]. Short-term forecasts are typically grouped into three methodological categories: time-series statistical models, machine learning techniques, and hybrid approaches [9].

Among traditional statistical models, ARIMA, GARCH, and ARMAX are widely used. Nogales et al. [11], using hourly data from the Spanish and Californian markets, showed that the transfer function model produced more accurate results than dynamic regression. Jakaša et al. [12] applied ARIMA models to EPEX data and obtained satisfactory results with proper parameterization. González et al. [13]

demonstrated that the Hilbertian ARMAX model outperformed the seasonal ARMAX model in terms of forecasting accuracy.

In reviewing prior works, we observe an evolution in forecasting strategies: early studies often relied on linear models (ARIMA variants), whereas more recent works increasingly employ machine learning and hybrid techniques to capture non-linear dynamics. Techniques such as Support Vector Machines (SVM), Random Forest (RF), Gradient Boosting, and Long Short-Term Memory (LSTM) networks have demonstrated success in modeling high-dimensional and complex relationships. Sansom et al. [14] showed that SVM outperformed ANN in forecasting using data from the Australian National Electricity Market. Mei et al. [15] emphasized the stable performance of RF under varying conditions, outperforming ANN and ARMA in real-time forecasts. Foruzan et al. [16] highlighted that while ANN captures nonlinear patterns effectively, SVM performs better in high-dimensional contexts. Zhang et al. [17] reported that DRNN provided more realistic forecasts than SVM in the New England electricity market. Albahli et al. [18], using IESO data from Ontario, Canada, demonstrated that XGBoost outperformed SVM and RF in both price prediction and cost reduction. Bitirgen and Filik [19], in their study on New York ISO data, concluded that XGBoost achieved lower error rates and shorter computation times than ARIMA. O'Leary et al. [20], using data from the Irish electricity market, compared RF, SVM, LSTM, CNN, K-NN, and CapsNet models. While CapsNet performed well, they found K-NN to be more effective due to training time and compatibility issues. Wang et al. [21] showed that RF adapted well to market fluctuations caused by renewables in Gansu Province, providing high prediction accuracy. Poggi et al. [22] compared AR, ARIMA, LSTM, SARMA, and XGBoost using German electricity market data and found that XGBoost delivered the highest forecasting accuracy. Silva et al. [23] compared DNN, LSTM, CNN, Gradient Boosting, and MLR under exceptional conditions such as COVID-19 and found CNN to yield the most accurate results. Tightiz et al. [24] improved XGBoost forecasts on ISO New England data through error correction and Bayesian optimization. Conejo et al. [25] applied a Wavelet-ARIMA approach on Spanish hourly data across seasons, and Carpio et al. [26] found it outperformed ARIMA in the Singapore market. Shafie-khah et al. [27] proposed a hybrid WT-ARIMA-RBFN model for the Spanish electricity market, demonstrating higher accuracy and reliability than single models. Cerjan et al. [28] improved short-term forecasts using a hybrid system combining MLP and calendar-based similar-day analysis on EEX data. Saini et al. [29] suggested a hybrid model based on LR and SVM. Tang et al. [30] developed a hybrid forecasting model using Lasso, RF, Gradient Boosting, SVM, BP Neural Networks, and LSTM for the Australian market. Zhou et al. [31] applied LSTM and SMBO-based hyperparameter optimization on EMD-decomposed data. Bhatia et al. [32] analyzed the effects of renewables and combined RF and XGBoost via bagging to achieve high accuracy and efficiency. Manfre Jaimes et al. [33] conducted multi-day forecasts using LSTM and XGBoost for the Alberta electricity market to support more profitable bidding strategies. A summary of the applied forecasting techniques is provided in Table 1.

Table 1: Summary of notable studies on electricity price forecasting in different markets

Reference	Method	Market	Models used
[11]	T	Spain and California Electricity Market	Dynamic Regression, Transfer Function
[34]	T	Spain and California Electricity Market	ARIMA
[14]	ML	Australian National Electricity Market	ANN and SVM
[25]	H	Spain Electricity Market	Wavelet-ARIMA

(Continued)

Table 1 (continued)

Reference	Method	Market	Models used
[12]	T	EPEX	ARIMA
[27]	H	Spain Electricity Market	WT, ARIMA and RBFN
[26]	H	Singapore Electricity Market	Wavelet-ARIMA
[15]	ML	New York ISO	RF, ANN and ARIMA
[28]	H	European Energy Exchange (EEX)	MLP and CWI
[16]	ML	New York ISO	ANN and SVM
[29]	H	Australian National Electricity Market	LR and SVM
[13]	T	EPEX	Hilbertian ARMAX
[35]	T	Australian National Electricity Market	LSTM and Adam Optimizer
[30]	H	Australian National Electricity Market	Lasso, RF, GB, SVM, BP ANN and LSTM
[31]	H	Pennsylvania–New Jersey–Maryland (PJM)	EMD, LSTM and SMBO
[17]	ML	New England ISO	DRNN and SVM
[18]	ML	IESO (Ontario, Canada)	XGBoost, RF and SVM
[19]	ML	New York ISO	XGBoost and ARIMA
[20]	ML	Irish Electricity Market (I-SEM)	RCF, SVM, LSTM, CNN, K-NN and CapsNet
[32]	HL	Australian National Electricity Market	RF, XGBoost and Bagging
[36]	T	European Electricity Market	LSTM
[21]	ML	Gansu Province, China	RF
[22]	ML	German Electricity Market	AR, ARIMA, LSTM, SARIMA and XGBoost
[23]	ML	Iberian Electricity Market (MIBEL)	DNN, LSTM, CNN, GB and MLR
[33]	H	Alberta Electricity Market (Canada)	LSTM and XGBoost
[37]	H	European Electricity Market	RF and LSTM
[24]	ML	New England ISO	XGBoost

Note: T: time series, ML: machine learning, H: hybrid models.

2.1 Studies on the Turkish Electricity Market

In the Turkish electricity market, both statistical and AI-based models have been utilized for day-ahead price forecasting. Adalı [38] applied regression and neural networks, while Biricik et al. [39] developed ANN-based short-term models using calendar, load, and weather data. Ugurlu et al. [40] reported successful results with GRU architecture, and Ertaylan et al. [41] emphasized the positive impact of data diversity on prediction accuracy. Demirezen and Çetin [42] found that RF outperformed SVM in day-ahead price forecasting. Boru İpek [43] demonstrated satisfactory results using ANN, CNN, XGBoost, CatBoost, and AdaBoost models in the energy sector. Arslan and Ertuğrul [44] reported the superior performance of neural networks, while Karatekin and Başaran [45] highlighted the advantages of XGBoost in terms of both accuracy and speed. Arifoglu and Kandemir [46] identified LSTM as the most effective model on average. Yorat et al. [47] showed that XGBoost produced better results than MLR and ARIMA in terms of error rates. Table 2 summarizes key studies conducted in recent years.

Table 2: Selected studies on day-ahead price forecasting in the Turkish electricity market

Reference	Method	Market	Models used
[38]	ML	TEİAŞ	Regression Analyze and ANN
[39]	ML	PMUM, Accuweather, Central Bank	ANN
[40]	ML	EXIST	ANN, CNN, RNN, LSTM and GRU
[41]	ML	EXIST	ANN
[42]	ML	EXIST	SVM and Random Forest
[43]	ML	EXIST	ANN, CNN, XGBoost, CatBoost and AdaBoost
[44]	H	EXIST	MLR, ANN and ARIMA
[45]	ML	EXIST	Linear Regression, Polynomial Regression, ANN and XGBoost
[46]	ML	EXIST	MLP, CNN, LSTM and GRU
[47]	ML	EXIST	MLR, ARIMA and XGBoost

Note: T: time series, ML: machine learning, H: hybrid models.

In conclusion, a wide range of methodologies including traditional statistical approaches, machine learning, and deep learning has been effectively applied to day-ahead price forecasting in the Turkish electricity market. This study highlights that forecasting outcomes vary considerably across different markets. For instance, while XGBoost demonstrated superior performance over SVM and RF in the Ontario market, in another case a deep learning model achieved promising results but was constrained by substantial training challenges. These observations indicate that the selection of an appropriate forecasting method must be informed by both the characteristics of the underlying data and the operational constraints of the application environment. Building on this premise, our study provides a comparative analysis within Turkish market, with particular emphasis on practical considerations such as computational efficiency and model interpretability. By positioning our work within the broader literature, we identify an emerging trend: although advanced ensemble and deep learning approaches are increasingly favored, their relative advantages remain dependent on market-specific conditions. This represents a critical gap that our research seeks to address in the Turkish market.

Beyond price-forecasting models, recent research has expanded to broader energy-management strategies that underscore the value of accurate forecasts. For example, Sui et al. [48] develop a day-ahead energy management system (EMS) for pelagic islanded microgrid groups that explicitly handles non-integer-hour inter-island energy transfers via electric vessels by coordinating "mirror" and original unit commitments within a 1-h schedule. Tan et al. [49] propose a robust day-ahead dispatch model for integrated electricity–heat networks that derives a linear district-heating network under a variable-flow/constant-temperature (VF–CT) strategy and embeds price-based integrated demand response using demand–price elasticity and thermal-sensation vote; formulated as a two-stage robust optimization, it co-optimizes prices and generation to hedge wind, ambient-temperature, and demand-response uncertainties. Sui et al. [50] present an optimal scheduling strategy for integrated electric–hydrogen systems that models continuous hydrogen-vessel transit and berthing times and exploits controllable grid components (e.g., UPFCs/switching) and overlying-ice effects; cast as a MILP and solved via decomposition, it reduces total energy-transfer costs by ≈12.9% in IEEE-RTS79/Jiangsu case studies. Finally, Xu et al. [51] introduce a VMD-based multi-attention feature-fusion model (V-MAF) that couples SE-TCN and SE-GRU with multi-head attention to capture multi-scale price/load patterns; on Singapore data it achieves RMSE = 1.3168 and reduces errors by 11–59% relative to XGBoost, ATT-CNN-LSTM, BiGRU, and VMD-Transformer.

In light of the above literature, our study contributes to the field in three significant ways: first, it demonstrates the applicability of XGBoost in a highly volatile market such as the Turkish electricity market; second, it presents a comparative analysis of various forecasting methods, highlighting their respective advantages and limitations; and third, it enhances the interpretability of model outputs through SHAP-based variable importance analysis. The findings indicate that such models can be effectively utilized in the decision-making processes of energy market stakeholders.

3 Method and Materials

This study aims to forecast the hourly day-ahead market clearing price (MCP) in the Turkish electricity market. To this end, a comparative analysis was conducted using several machine learning models. No artificial intelligence (AI) tools were used in the preparation of data or analysis of this study; all work was conducted by the authors.

Dataset Description: The study utilizes hourly data from 2023, comprising 8760 observations of the Turkish day-ahead market clearing price (in TRY) and related features. Key input variables include total electricity demand, generation by source (natural gas, coal, hydro, wind, etc.), weather factors (e.g., hourly temperature), and calendar indicators (weekday/weekend and holiday flags). All price and generation data were obtained from Energy Exchange Istanbul (EXIST), and weather data (temperature) were sourced from the Turkish State Meteorological Service, ensuring real-world relevance.

During the data preprocessing phase, missing values were completed using appropriate imputation methods. In addition, categorical variables such as weekday/weekend, month, and hour were encoded and formatted to be suitable for model input.

3.1 Applied Forecasting Models

The following forecasting algorithms were implemented and their performances were compared:

LSTM (Long Short-Term Memory): A deep learning architecture capable of learning long-term dependencies in time series data. It was developed to overcome the vanishing gradient problem observed in classical RNNs. LSTM cells regulate information flow through input, forget, and output gates, enabling the network to retain critical past information over extended periods and learn complex sequential patterns.

SVM (Support Vector Machines): Support Vector Machines are supervised learning algorithms used for both classification and regression tasks. In the context of regression referred to as Support Vector Regression (SVR) the model aims to determine an optimal hyperplane that fits the data within an epsilon-insensitive margin, minimizing prediction error while maintaining model simplicity. SVM's capability to handle non-linear relationships is enabled through the use of kernel functions, which map input data into higher-dimensional feature spaces. In this study, the Radial Basis Function (RBF) kernel was employed and yielded the most accurate results.

Random Forest (RF): An ensemble learning method that constructs multiple decision trees using random subsets of data and features. The final prediction is obtained by averaging the outputs of individual trees. This structure reduces overfitting and yields stable results in high-dimensional datasets.

Gradient Boosting (GBM): This technique sequentially builds weak learners (typically decision trees) to reduce prediction errors. Each subsequent model is trained to correct the errors of its predecessor. Key hyperparameters, such as the learning rate and maximum depth, greatly influence the model's performance.

XGBoost (Extreme Gradient Boosting): XGBoost is an optimized, regularized implementation of gradient-boosted decision trees noted for speed, scalability, and strong predictive accuracy. It parallelizes split-finding, handles missing values via sparsity-aware default directions, and applies both L1 and L2 regularization (along with shrinkage and subsampling) to control overfitting [7].

3.2 Performance Evaluation Metrics

To objectively assess the performance of the forecasting models, the following error metrics were employed:

MAE (Mean Absolute Error): The average of the absolute differences between actual and predicted values. A lower MAE indicates that the model has a lower average prediction error.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i, \hat{y}_i| \tag{1}$$

MSE (Mean Squared Error): The average of the squared differences between actual and predicted values. This metric penalizes larger errors more heavily, making it sensitive to outliers.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i, \hat{y}_i)^2 \tag{2}$$

RMSE (Root Mean Squared Error): The square root of the MSE. It shares the same unit as the predicted variable, making it easier to interpret.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i, \hat{y}_i)^2} \tag{3}$$

R2 (Coefficient of Determination): Indicates the proportion of variance in the dependent variable that is explained by the model. A value closer to 1 implies a higher explanatory power.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{4}$$

3.3 Hyperparameter Optimization

The predictive performance of the XGBoost model largely depends on the effective tuning of its hyper-parameters. Therefore, in this study, the *RandomizedSearchCV* method was employed for hyperparameter optimization. This method evaluates randomly selected combinations within the predefined ranges shown in Table 3.

Table 3: Hyperparameter ranges used in the optimization process

Hyperparameter	Description	Range
Number of estimators	Number of boosting iterations	100, 300, 500
Maximum tree depth	Maximum depth of individual trees	3, 5, 7
Learning rate	Controls the contribution of each tree	0.01, 0.05, 0.1
Subsample ratio	Fraction of training data used per boosting iteration	0.6, 0.8, 1.0
Column sample by tree	Fraction of features used per tree	0.6, 0.8, 1.0

To ensure a robust evaluation of model performance, 5-fold cross-validation was conducted. We observed that the model's performance was relatively stable for small changes in hyperparameters around the optimal values. For instance, altering XGBoost's learning rate by ±0.02 or maximum tree depth by ±1 from the chosen settings changed the RMSE by less than 1%. This indicates the model is not unduly sensitive to minor tuning differences, lending confidence that our chosen parameters are robust. The hyperparameter combination that achieved the highest overall performance across the validation folds was selected for the final model.

3.4 SHAP Analysis

To improve the interpretability of the XGBoost model's predictions, the SHapley Additive exPlanations (SHAP) method was employed. SHAP is based on Shapley values from cooperative game theory and quantitatively determines the contribution of each input variable to the model's output. It also provides a visual representation of these contributions.

This approach allows for a clear understanding of which variables influence the model and to what extent they affect the predictions. As a result, the model not only achieves high forecasting accuracy but also ensures transparency and interpretability in the decision-making process.

4 Implementation and Forecasting Results

This section presents the experimental findings obtained from the implementation of the theoretical approaches and machine learning models previously detailed in the methodology, aimed at forecasting day-ahead electricity prices in the Turkish electricity market. The dataset used in the implementation consists of 8760 hourly observations (one year of data) from the Turkish electricity market. Of this, 80% was allocated for model training and the remaining 20% (1752 entries) for testing. A rolling forecasting origin was utilized for model evaluation: starting with an initial training period (the first 80% of data, January–September 2023), models were retrained at regular intervals (monthly) as new data became available, and day-ahead forecasts were generated for the next period. This walk-forward approach ensured that each test prediction was truly out-of-sample. Notably, the dedicated test set (the final 20% of data, October–December 2023) remained completely unseen during model training and tuning, providing a strict out-of-sample evaluation. The implementation was carried out in the Python Jupyter Notebook environment, utilizing core libraries such as pandas, numpy, matplotlib.pyplot, sklearn.metrics, and time throughout the modeling process. A comparative summary of the models' performances is presented in Table 4.

Table 4: Performance comparison of forecasting models

Metric/Models	LSTM	SVM	RF	Gradient boosting	XGBoost
MAE	295.09	172.53	159.91	152.75	144.79
MSE	144,192	55,932	50,400	44,695	40,704
RMSE	379.72	263.5	224.5	211.41	201.75
R2	0.528	0.894	0.905	0.915	0.923
Training Time (S)	462.23	119	1017.8	393.61	94.12
Forecasting Time (S)	1.27	2	0.21	0.25	0.02

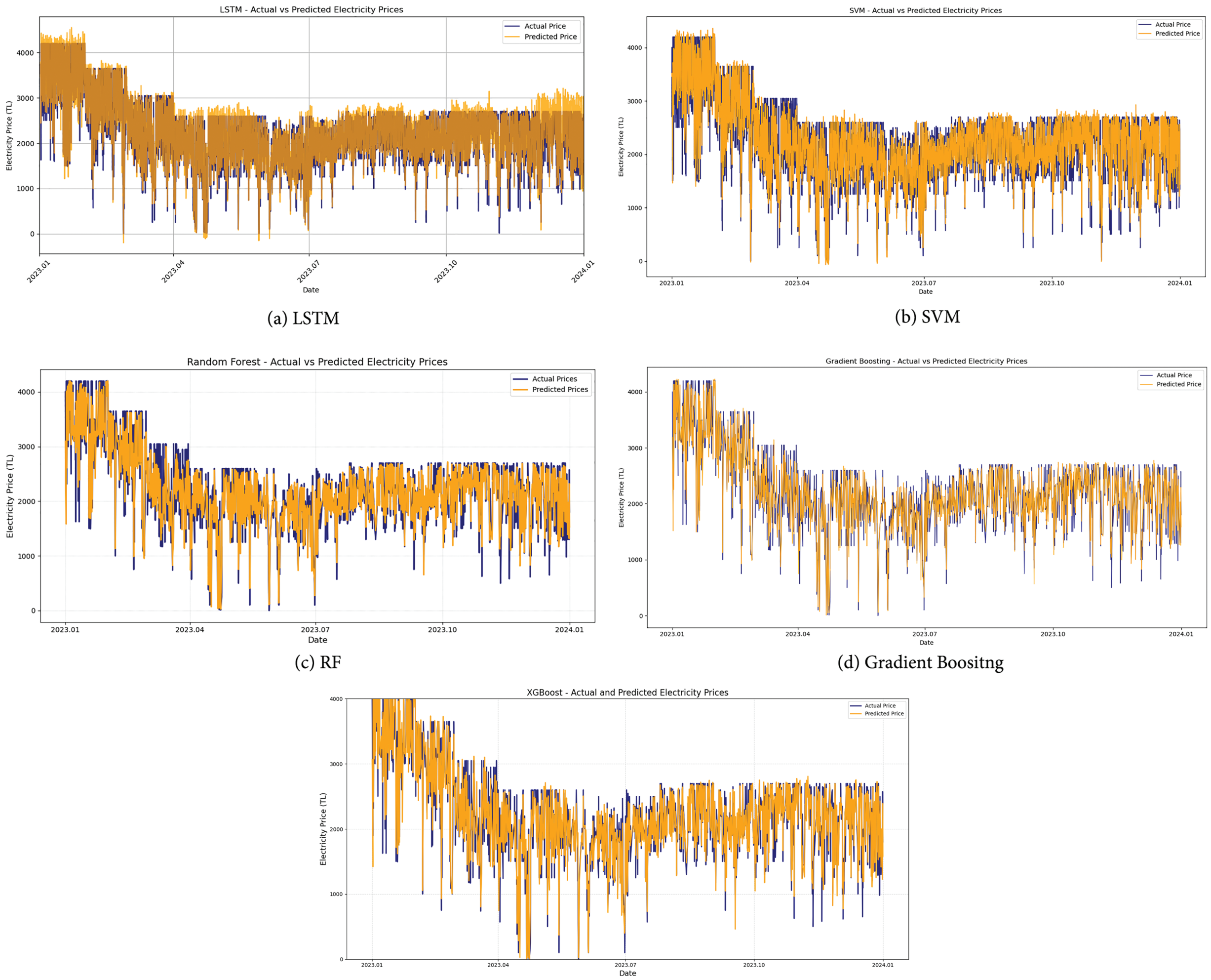
An examination of Table 4 reveals that five models were evaluated based on MAE, MSE, RMSE, R^2, training time, and prediction time. Among these, the XGBoost model achieved the best overall performance, with MAE (144.79), MSE (40,704), RMSE (201.75), and R^2 (0.923). The Gradient Boosting model also performed well (MAE: 152.75; RMSE: 211.41; R^2: 0.915), although it fell slightly behind XGBoost. The Random Forest model yielded satisfactory results (MAE: 159.91; RMSE: 224.5) but required significantly longer training time, making it less favorable for real-time applications. The LSTM model showed moderate success, outperforming traditional methods with MAE (295.09), RMSE (379.72), and R^2 (0.528), though its high MSE (144,192) suggests considerable deviation in its forecasts. While the SVM model achieved a relatively high R^2 (0.894), its RMSE (263.5) and MSE (55,932) indicate susceptibility to higher errors in certain scenarios (Note: All error metrics are in Turkish Lira. For international context, the average exchange rate in late 2023 was approximately 1 EUR ≈ 25 TL. Thus, for example, XGBoost's MAE of 144.79 TL corresponds to about 5.79 EUR).

To determine if the performance differences are statistically significant, we conducted a Diebold-Mariano (DM) test comparing XGBoost with the second-best model (Gradient Boosting) using their one-day-ahead forecast error series. The DM test yielded a statistic of 2.11 with a p-value of 0.035, indicating that XGBoost's error improvements are statistically significant at the 5% level. In other words, the probability that XGBoost's better performance is due to random chance is only ~3.5%. This confirms that XGBoost's advantage is robust.

LSTM predictions in Fig. 1a are relatively accurate during stable periods but deviate significantly at the extremes. As shown in Fig. 1b, SVM is successful in capturing high-price episodes, although prediction errors increase during sudden changes. Fig. 1c shows that Random Forest can generally follow market trends but exhibits unexpected deviations during periods of high volatility. In Fig. 1d, the Gradient Boosting model demonstrates strong trend-tracking ability, although it sometimes reacts with a delay at peak points.

The forecast performance of the XGBoost model is detailed in Fig. 1e, which confirms its ability to capture both overall trends and sudden shifts in electricity prices. The model's low MAE and RMSE reinforce its consistency and reliability.

All experiments were run on a standard PC with an Intel Core i7-9700 CPU (3.0 GHz) and 16 GB RAM; no GPU acceleration was used. In terms of computational cost, the results in Table 4 show that the deep learning model (LSTM) required substantially longer training time (~462 s). XGBoost achieved its superior accuracy with a relatively low training time (≈94 s), highlighting its computational efficiency. The Random Forest model, although accurate, took the longest to train (~1018 s), making it less practical for real-time use. These hardware and timing details illustrate the trade-off between accuracy and speed: XGBoost and Random Forest provided high accuracy, but XGBoost did so with far less computation.



(a) LSTM

(b) SVM

(c) RF

(d) Gradient Boositng

(e) XGBoost

Figure 1: Actual vs. forecasted electricity prices using the compared models

4.1 Graphical Comparative Analysis

Fig. 2 provides a visual comparative analysis of the models' performance across MAE, MSE, RMSE, R^2, training time, and prediction time. The intensity of colors in the figure reflects the models' relative success across metrics, clearly demonstrating that XGBoost outperforms all others. Although Gradient Boosting and Random Forest are competitive in terms of accuracy, they lack XGBoost's efficiency in computation time. LSTM and SVM may be preferred in specific use cases, but ARIMA fails to deliver satisfactory performance either in terms of accuracy or interpretability.

4.2 SHAP Analysis

To enhance the interpretability and reliability of the most successful model, SHAP analysis was conducted for XGBoost. As shown in Fig. 3 (Beeswarm plot), the most influential variable on electricity price forecasting is the volume of electricity generated from natural gas. The plot highlights both the positive and negative directional impacts of variables, aiding in understanding the model's decision-making processes.

Figure 2: Comparison matrix of the models based on performance metrics

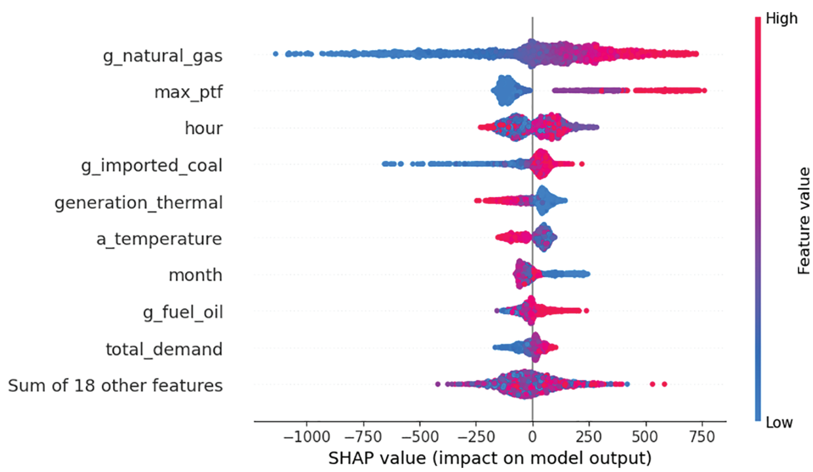


Figure 3: Beeswarm plot of the SHAP method for the XGBoost model

Fig. 4 presents the SHAP bar plot, ranking the features by their average absolute impact on the output. Natural gas-based electricity generation stands out as the most influential factor, followed by the monthly maximum market clearing price (max_ptf), hour of the day, imported coal-based electricity generation, and average temperature. These insights can guide market actors and regulators in understanding and potentially intervening in price formation mechanisms.

Fig. 5 displays a SHAP dependence plot, indicating a nonlinear, threshold-based relationship between natural gas-based electricity generation and price forecasts. Notably, when production exceeds 5000 MWh, the SHAP effect becomes strongly positive, underscoring the fragility of the supply-demand equilibrium. This insight can be valuable in shaping strategic energy policies and cost-efficient production planning.

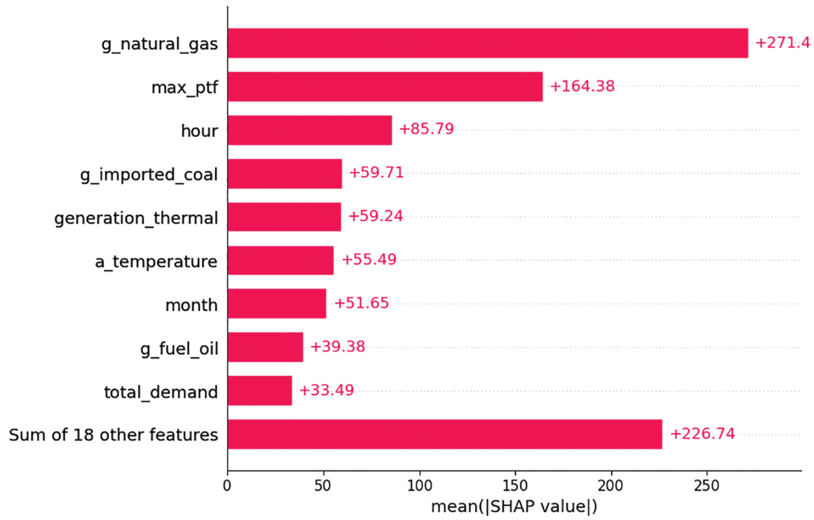


Figure 4: SHAP bar plot for the XGBoost model

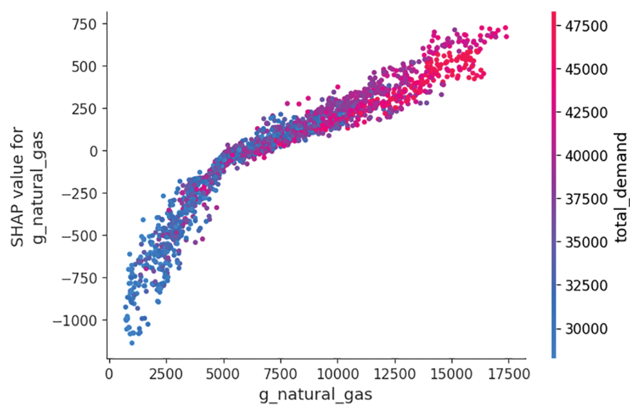


Figure 5: Dependence plot of natural gas-based electricity generation in the XGBoost model using the SHAP method

In conclusion, the application of various models for day-ahead electricity price forecasting in the Turkish market revealed that XGBoost stands out with its high accuracy, fast computation time, and strong interpretability. These findings provide actionable insights and strategic decision support for stakeholders in the energy sector. It is important to acknowledge the limitations of this study. First, the analysis was conducted on a single year of data from one market (Turkey); while this provided interesting insights, the models' performance and the SHAP interpretations might differ under other market conditions or with more extensive datasets. Second, although we included several exogenous features (e.g., temperature, generation by source), other factors such as public holidays or fuel prices were not incorporated and could be explored in future research.

5 Conclusion

This study demonstrated that among various forecasting methods, the XGBoost algorithm achieved the highest accuracy in predicting day-ahead electricity prices in the Turkish market, with the lowest RMSE of approximately 201.8 TL (≈8 EUR) and an R^2 of 0.923. Compared with alternative models such as SVM and LSTM, XGBoost proved more effective in capturing complex nonlinear dynamics, while the SHAP analysis provided valuable interpretability by identifying natural gas generation, maximum market clearing price (max_ptf), hour of the day, imported coal generation, and average temperature as the most influential drivers of price fluctuations.

The results imply that ensemble learning methods like XGBoost can effectively address the challenges of volatile electricity markets by offering both predictive accuracy and transparency. For practitioners, the speed and reliability of the model suggest that it could be deployed in real-time pricing and operational planning systems, supporting risk management and more informed decision-making. At the academic level, this work contributes to the energy forecasting literature by illustrating the dual benefit of accuracy and interpretability, which is increasingly valued in modern power system analytics. Although our case involves only dozens of input variables, XGBoost scales well to high-dimensional data. Even with thousands of predictors, its tree-splitting tends to ignore irrelevant variables and focus on the most informative ones an implicit form of feature selection. Training is also parallelizable. We therefore expect strong performance to carry over to larger problems, albeit with longer training times and higher memory use.

Certain limitations should be acknowledged. The analysis was restricted to a single-year dataset from one market, which constrains the generalizability of the findings. The study also followed a deterministic forecasting framework without incorporating probabilistic measures such as confidence intervals, which would be valuable for risk-sensitive applications. Future research should therefore expand to multi-year and multi-market datasets, integrate additional exogenous variables such as holidays, fuel prices, and macroeconomic indicators, and test hybrid or probabilistic models to improve robustness. Extending the use of SHAP or similar tools for example, through interactive dashboards could further support transparent decision-making and bridge forecasting research with practical applications.

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