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Balancing Accuracy and Interpretability: GradientSHAP for Enhanced Energy Demand Predictions

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ABSTRACT

The growing amalgamation of renewable sources of energy in power systems has increased the need for accurate energy demand prediction within smart grids. Recent progress in machine learning has improved predictive capabilities; however, most of these models are complex in structure and lack interpretability. This study proposes a novel GradientSHAP which fuses gradient boosting algorithms with SHAP (SHapley Additive exPlanations) values to enhance predictive performance while improving model interpretability. GradientSHAP is developed to capture complex ad non-linear structure in the time-series and weather data for a robust energy demand predictions. SHAP values are computed together with the boosting algorithm to provide meaningful information into the impact of the individual features on the model predictions. The European energy demand dataset is utilized in this study to evaluate the proposed GradientSHAP, and the model performance is compared with traditional models such as linear regression and support vector regression (SVR). GradientSHAP outweighs these traditional models, obtaining the lowest training and test Mean Squared Error (MSE) and the highest R-squared (R^2) score, demonstrating optimal predictive capability. Detailed and concise explanation of feature contributions is presented via SHAP plots to enhance model transparency. The proposed GradientSHAP achieves a significant milestone in energy demand prediction and demonstrates a substantial ability to balance high predictive accuracy and interpretability without a trade-off, which is essential in predicting energy demand in smart grids.

***Keyword**:* GradientSHAP, Machine Learning, Energy Demand, Smart Grid, Time-series.

1. INTRODUCTION

Precise and accurate prediction of energy demand is paramount for optimizing resource allocation, sustaining grid stability, and planning energy production within smart grids [1]. Solar and wind are the two renewable sources of energy integrated into the electricity system generation, leading to a hike in the variability and complexity of energy demand, necessitating reliable and automatic predictive models [2]. Traditional approaches often lack the capacity to capture intricate dependencies and convoluted temporal interactions necessary for energy demand prediction [3]. Current innovations have demonstrated that leveraging ML algorithms enhance predictive capabilities by capturing complex representations in large datasets [4]. However, the major disadvantages are model complexity and limited interpretability. To mitigate these drawbacks, we propose a novel approach called GradientSHAP, a lightweight model for enhancing predictive accuracy and providing interpretability. The goal of GradientSHAP is to provide transparent interactions between features for the prediction of energy demand, ultimately helping practitioners to understand how various constituents impact energy demand. The following are the main contributions of this research:

- This paper introduces the GradientSHAP model, which combines Gradient Boosting and SHAP values to forecast energy demand with enhanced accuracy and interpretability.
- Explainable AI is incorporated to provide meaningful details into the feature interactions.
- This research offers concise evaluation of other ML algorithms on energy demand prediction and compares the performance of the proposed GradientSHAP with other models.
- Analyzes the time-series feature selection and imputation techniques critical to enhancing the model performance.

- Utilization of SHAP techniques to enhance model interpretability, offering precise understanding of how individual features impact and contributes to the predictions.

The subsequent parts of this study are organized as follows; section 2 provides a detailed literature review of related approaches in energy demand prediction. The proposed methodology is explained in section 3 which details the data gathering process, feature selection, and concise explanation of the proposed GradientSHAP. It also explains the data preprocessing steps and model selection criteria. Section 4 presents the performance analysis of the models, discusses the significance of each evaluation metric, and provides visualizations such as residual distributions and violin plots to assess model performance. Section 5 concludes the key findings and advantages of the GradientSHAP model and provides recommendations for its implementation in real-world energy forecasting scenarios. Finally, the paper outlines the limitations of the current study and proposes directions for future research to enhance energy demand forecasting using GradientSHAP in section 6.

2. RELATED WORK

Recent advancements in machine learning (ML) have significantly contributed to the accuracy and reliability of energy demand forecasting within smart grids. This section summarizes prior literature on energy demand forecasting. Recent advancements in solar irradiance and power forecasting have utilized a range of methodologies. Zambrano and Giraldo [1] proposed forecasting models that do not rely on on-site measurements, offering an advantage for remote areas; however, their accuracy depends on the availability of comprehensive weather data. Sobri et al. [2] conducted an extensive review of solar photovoltaic (PV) forecasting methods, concluding that machine learning (ML) techniques significantly improve forecast accuracy but are often complex and computationally demanding. Voyant et al. [3] evaluated various ML approaches for solar radiation prediction and spotted their high prediction accuracy; however, data limitation for training data was a setback. Agüera-Pérez et al. [4] analyzed weather prediction for micro-grid maintenance, pointing that weather predictions enhances energy distribution but fast-changing weather conditions posed a drawback. Qazi et al. [5] reviewed the efficacy of neural networks for solar prediction, disclosing the need for optimal data quality. Antonanzas et al. [6] investigated the use of ML for photovoltaic (PV) electricity prediction and reported the advantages of ML approach, although, requires thoughtful model selection. Das et al. [7] concentrated on model optimization to enhance predictive accuracy for PV electricity generation and demand.

Yadav and Chandel [8] explored the utilization of neural network techniques in solar prediction, demonstrating satisfactory outcome, with drawbacks in extreme hyperparameter tuning. Özge and Ümmühan [9] investigated solar radiation and electricity prediction strategies and reported difficulties associated with obtaining reliable prediction under changing weather conditions. Zendehboudi et al. [10] implemented support vector machine models to predict solar and wind energy, obtaining optimal accuracy but encountered difficulty in generalizing across various geographic settings. Notably, Huang et al. [11] and Lorenz et al. [12] integrated multiple algorithms and remote sensing information to predict hourly energy demand, however, handling dynamic weather variations was a challenge. In recent development in photovoltaic (PV) electricity output prediction, Raza et al. [13] highlighted major advancement in prediction approaches using ML algorithms and weather datasets. However, adaptability of these models to the changing weather conditions was a drawback. Huang et al. [14] proposed an automated model using weather-based prediction for one-day-ahead hourly forecast of PV electricity generation, establishing enhanced prediction accuracy.

Nevertheless, the model faced limitations with computational intensive when handling large-scale datasets. Rozas Larraondo et al. [15] built a circular regression tree-based model for airport weather forecasting, which effectively captured cyclical data sequence. Irrespective of the enhanced performance obtained, scalability for larger geographical areas were a challenge. Qing and Niu [16] proposed a novel strategy for predicting solar irradiance based on hourly day-ahead and weather forecasts utilizing Long Short-Term Memory (LSTM) model. Their approach outweighed traditional machine learning algorithms in temporal pattern learning, but requires extensive computational resources.

Akarslan and Hocaoglu [17] put forward a similarity-based approach to forecast hourly solar irradiance. However, the accuracy of the model dropped for prolong forecasting periods. Gigoni et al. [18] proposed a method to enhance the accuracy and reliability of forecasting PV electricity generation based on 24 hours-ahead, but faced with the limitations of testing the model in real-world varying PV plant settings. In another study, Semero et al. [19] investigated a fusion approach of Genetic Algorithm, Particle Swarm Optimization for PV electricity forecasting. This fusion strategy enhanced prediction performance, however, the model complexity resulted in extensive computational. Zhang et al. [20] explored 24 hours-ahead power output prediction for small-scale solar PV power generation. The study revealed the drawbacks associated with varying solar generation and investigated a forecasting strategy that mitigates prediction errors; however, further research was necessary to adapt the approach to a broader context of PV equipment.

3. METHODOLOGY

This section presents the different approaches employed to achieve optimal energy demand prediction. These approaches are data gathering, preprocessing time-series and weather data, selecting meaningful feature representations, model training, and evaluating.

3.1. Data Collection

The dataset utilized in this study is sourced from the open power system data (OPSD) platform of European power systems, containing time-series load and weather data. The time-series load dataset contains hourly electricity load information, including actual power consumption and predicted load across various European regions, spanning over years, which is essential for comprehending demand sequence and predicting future electricity consumption. The data includes time-stamped load information, which is essential for constructing time-dependent sequence and seasonal variations in electricity consumption. It also consists of other variables such as electricity prices, generation from renewable sources (solar and wind), and other important time-based characteristics.

The weather data comprises hourly meteorological elements such as temperature, wind speed, and solar radiation. The interactions of weather elements with the time-series variables ensure concrete assessment of weather impacts on power generation and usage. Both datasets comprise of timestamps as overlapping features, which is ideal constructing and training predictive models that leverage the sequential pattern of electricity usage and weather change over time.

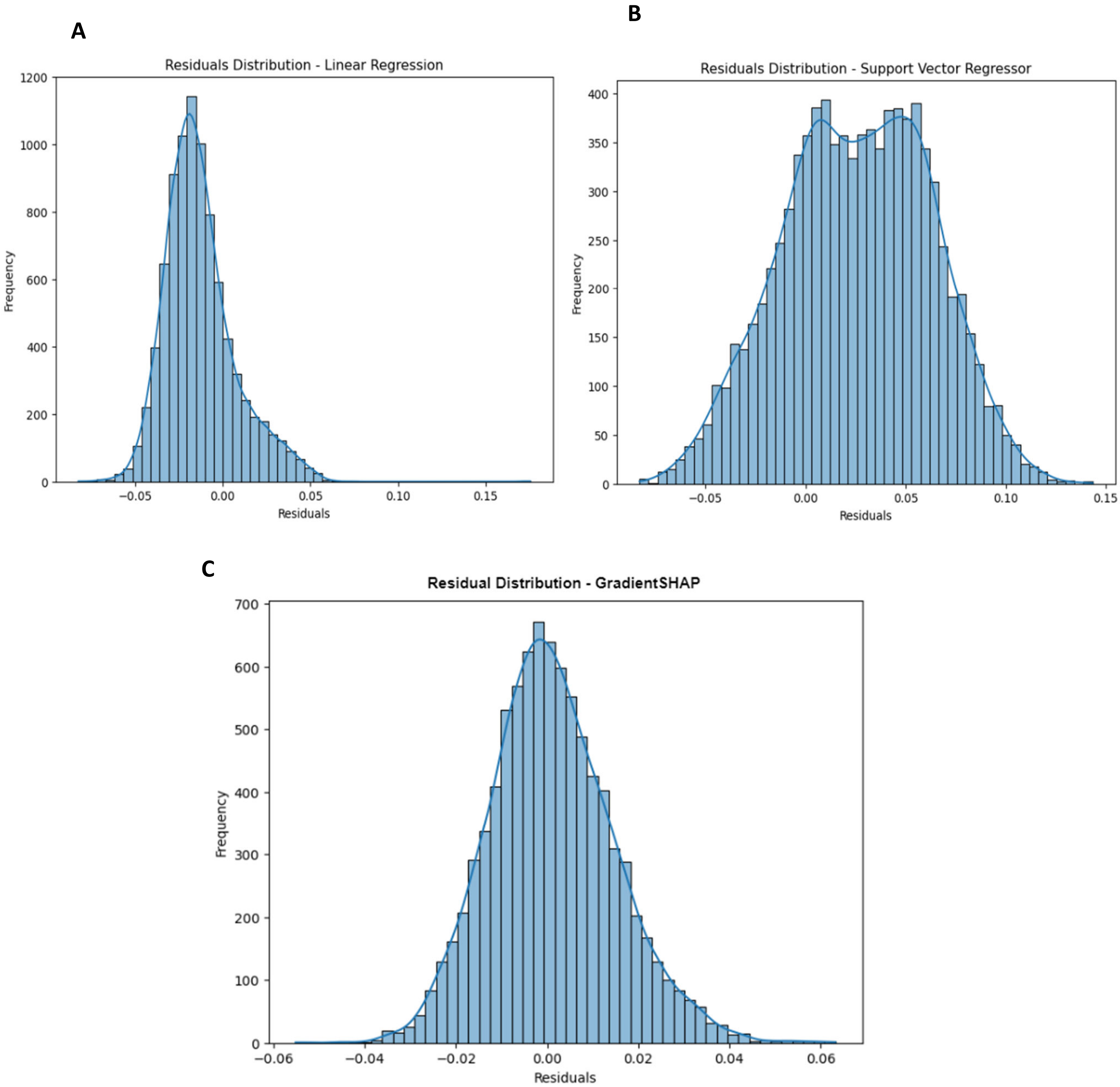


Figure 1A-C. Residual distribution of the different models.

3.2. DATA PREPROCESSING

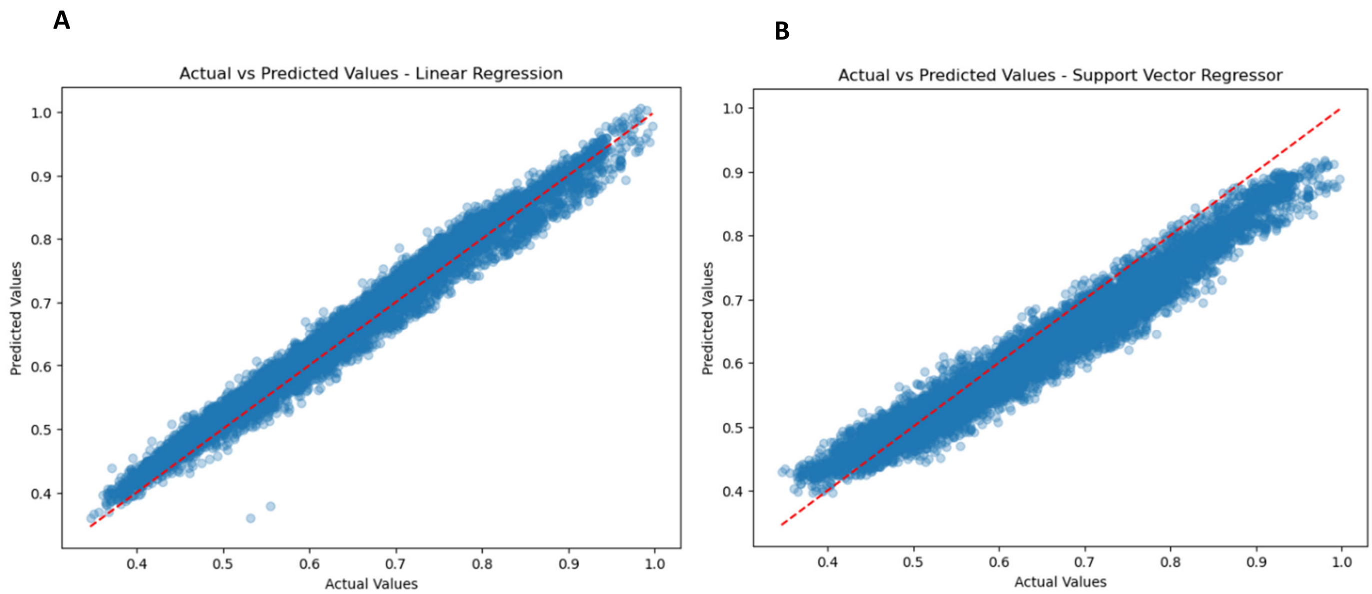
This study adopted several vital processes to ensure that the data is denoised, consistent, and compactable for training the proposed model. First, the datasets consisting of both the time-series and weather were loaded into the environment using necessary libraries, and an initial validation is conducted to comprehend the data structure, pattern of the columns, data types, and perpetual problem associated with null values.

Essential variables such as electricity demand and weather indicators with missing elements were imputed utilizing forward-filling and interpolation to preserve continuity in the time-series data without including bias. The timestamp columns were changed to date-time element to necessitate time-based process, ensuring consistency in data.

Each respective timestamps for time-series and weather data are merged to maintain matching correspondence for each hourly input and ensure both cover the same periods. To capture temporal features pattern in electricity consumption, we extracted elements such as hour, day of the week, months, and season from the timestamp. We generated lag feature such as electricity demand in previous hours to obtain temporal dependency to help the model comprehend patterns over time. More so, we normalize the numerical features to ensure uniform range for all features to help enhance the model convergence in the training phase. Finally, we split the preprocessed dataset into training and test sets, maintain temporal pattern essential for training the proposed model.

3.3. Model Selection

This research evaluates a diverse range of ML model in comparison to the proposed model for predicting energy demand. Initially, linear regression is employed as a baseline model, known for its simplicity and interpretability, where the relationship between features and the target variable is assumed to be linear. Support Vector Regression (SVR) is then utilized, which operates by mapping data to a higher-dimensional space to capture non-linear patterns, while aiming to minimize error within a defined margin. However, SVR may require significant tuning of hyperparameters to achieve optimal performance. GradientSHAP is included as a boosting algorithm, which sequentially builds models to correct errors made by preceding models, effectively reducing bias and variance. The selection of these models aims to capture both linear and complex non-linear relationships within the data. The final decision on the best model is based on the evaluation metrics like Mean Squared Error (MSE), R^2 Score, and additional metrics from visualizations, which help determine which algorithm generalizes best to unseen data while maintaining computational efficiency.



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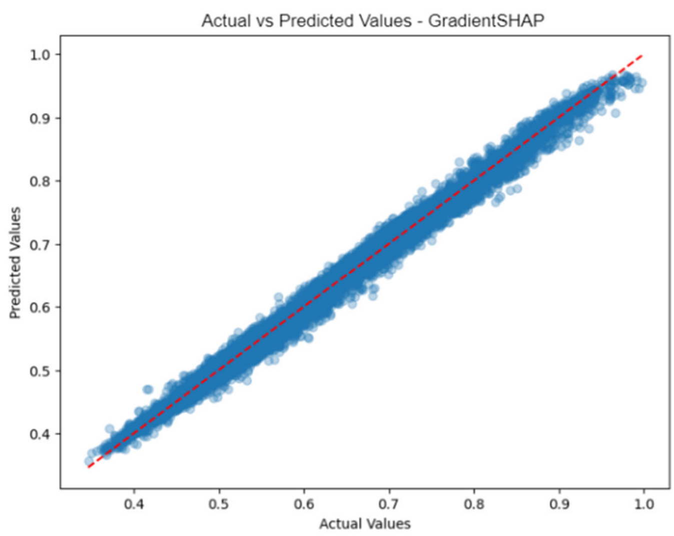

Figure 2A-C. Model performance evaluation plots for the different models.

3.4. Model Training and Evaluation

The model training and evaluation process involves several key steps to ensure that the machine learning algorithms learn effectively from the data and are evaluated accurately. The training phase begins with preprocessing the data, where missing values are handled using imputation techniques, and features are normalized and scaled. The imputed and preprocessed training data is then split into training features and target variable. The models are trained on training features using supervised learning algorithms where the goal is to minimize the error between the predicted output and the actual target values in the target variable. During training, the linear regression algorithm fit a model in equation 1.

$$(1) \qquad \hat{y} = X\beta + \in$$

Where $\hat{y}$ is the predicted value (target variable) and X is the training feature, β is the coefficient vector, and $\in$ is the error term. The model tries to find the best value of β that minimizes the residual sum of squares (RSS) whereas algorithms such as support vector regression (SVR), try to find a function that maximizes the margin while keeping prediction errors within a defined range as presented in equation 2. GradientSHAP employ iterative techniques to build ensemble models where each new model corrects the errors of previous ones by minimizing a loss function, often the Mean Squared Error (MSE), which reduces both bias and variance to improve model generalization as given in equation 2.

$$(2) \qquad f(x) = w^T X + b$$

Where w^T denotes the weight transpose vector and b is the bias term. The goal is to minimize the regularized hinge loss function.

$$(3) \qquad MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2$$

Where y_i denotes the true target values, $\hat{y_i}$is the predicted values, and n is the number of observations.

After model training, the performance is evaluated using both the training and testing data as presented in equation 3. R² score is a measure of the proportion of variance in the dependent element that is predictable from the independent element.

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

Where $\sum_{i=1}^{n}(y_i - \hat{y_i})^2$is the sum of squared residuals, $\sum_{i=1}^{n}(y_i - \bar{y})^2$is the total sum of square while $\bar{y}$ is the mean of the actual values. R^2 values range from 0 to 1, where a higher value indicates a better fit of the model. In this context, R^2 shows how much of the variance in mechanical properties can be explained by the model's features, thus providing a sense of how well the model generalizes to unseen data.

$$(5) \qquad MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

It is worth mentioning that the model with lowest MSE/RMSE and highest R^2 is the top-performing model. Further fine-tuning of hyperparameter is applied to the top-performing model to enhance predictive performance.

4. RESULT AND DISCUSSION

The predictive capability of the proposed GradientSHAP in comparison to other ML models is analyzed and discussed in this section. The residual distribution plots for the traditional models in comparison with the proposed GradientSHAP are shown in Figure 1 providing insights into the differences between the actual and predicted variables. A closely and narrow distribution of features around zero, as seen in Figure 1C, demonstrates the predictive ability of the proposed GradientSHAP, indicating satisfactory model accuracy and less prediction error. The LR plot also shows a relatively narrow distribution, showing acceptable predictive performance. However, the SVR plot displays a sparse distribution, indicating larger errors and reduced predictive accuracy compared to the proposed model. Table 1 shows the statistical analysis of the results obtained by all the models. The LR model achieved a strong predictive performance with a low training MSE of 0.0002 and a test MSE of 0.0006, indicating that the model generalizes well from training to test data. The high R^2 score of 0.9688 implies that the model captures 96.88% of the variance in the target variable. The MAE of 0.0205 and RMSE of 0.0241 confirm that the predictions are close to actual values, suggesting that linear regression is an efficient baseline model for this prediction. Another ML model adopted in this study is the SVR, on the other hand, performs adequately but with a noticeable reduction in accuracy compared to linear regression. It achieved a training MSE of 0.0018 and a test MSE of 0.0020, indicating some overfitting.

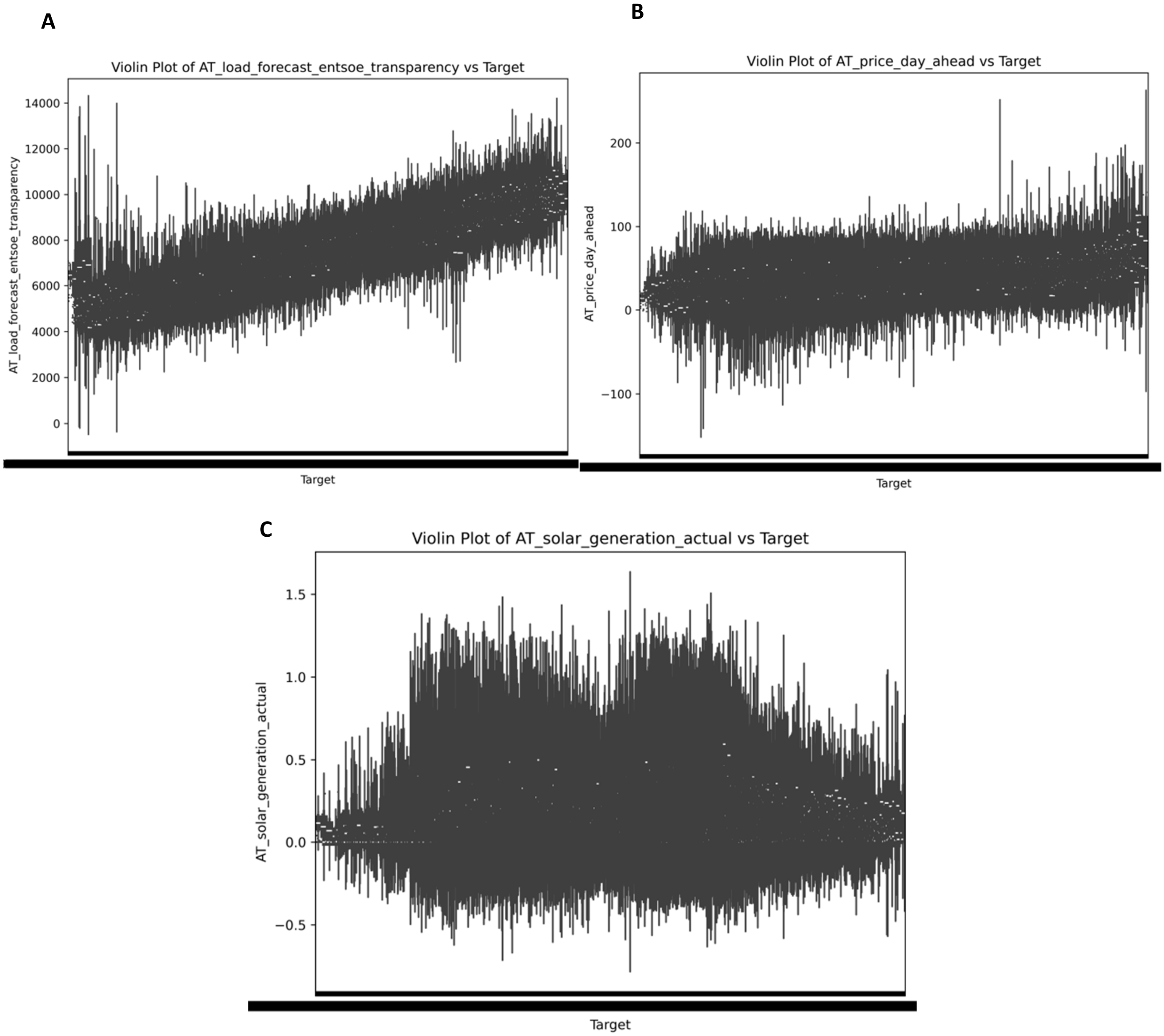

Figure 3A-C. Violin plots for the of GradientSHAP model.

The R^2 score of 0.8910 suggests that 89.10% of the variance is captured, which is lower than linear regression. This reduction in performance may be due to the SVR's kernel-based approach, which struggles with the complexity and high dimensionality of the data. The MAE of 0.0369 and RMSE 0.0451 achieved by the SVR indicate larger prediction errors. The GradientSHAP outperformed both linear regression and support vector regressor models, with an exceptionally low training and test MSE of 0.0002, suggesting minimal overfitting. The R^2 score of 0.9899 demonstrates that the model captures nearly 99% of the variance, making it the most accurate model in analysis.

The ability of gradient boosting to learn complex patterns in the data through an ensemble of weak learners allows it to achieve superior results, outperforming LR and SVR in accuracy and generalization. Overall, gradient boosting emerges as the best-performing model, with linear regression providing a strong baseline and SVR showing moderate effectiveness but higher error rates.

Figure 2 illustrates the errors (residuals) between the actual and predicted values for each model. The residuals for the linear regression model are centered on zero and normally distributed, indicating a strong fit. The SVR displays a wider spread in its residuals, suggesting higher prediction errors, while the GradientSHAP has a residual distribution tightly clustered around zero, signifying minimal error and a better prediction performance. Overall, the residual distribution plots highlight the GradientSHAP's superior accuracy over the other two models due to its smaller and more centered residuals.

Table 1. Result comparison of GradientSHAP with different machine learning models.

Model	**Train MSE**	**Test MSE**	**R^2 Score**	**Mean Absolute Error (MAE)**	**Root Mean Squared Error (RMSE)**
Linear Regression	0.0002	0.0006	0.9688	0.0205	0.0241
Support Vector Regressor (SVR)	0.0018	0.002	0.891	0.0369	0.0451
GradientSHAP	0.0002	0.0002	0.9899	0.0107	0.0138

The violin plots presented in Figure 3 provides insights into the distribution of the features with respect to the target variable. In the first plot for ‘AT_load_forecast_entsoe_transparency,’ the feature demonstrates a range of spread across the target values, suggesting a strong relationship and variability. The second plot, ‘AT_price_day_ahead,’ shows a somewhat stable distribution with less variation, indicating a potential weak or stable relationship with the target. Finally, the ‘AT_solar_generation_actual’ plot indicates a wider spread in the middle, implying that solar generation might have varied influence on the target at different levels. These plots help understand the impact and spread of individual features on the target.

The SHAP force plot visualizes how features impact the model's prediction as presented in Figure 4. The plot begins from the base value (0.632), with each feature either pushing the prediction higher (in red) or lower (in blue). The "AT_price_day_ahead" with a value of 62.0 slightly increases the prediction, while "AT_load_forecast_entsoe_transparency" with a value of 5511.0 significantly decreases it, resulting in an overall lower prediction. The length of the bars indicates the magnitude of the impact, providing insights into which features drive the model's prediction and how they influence the final output.

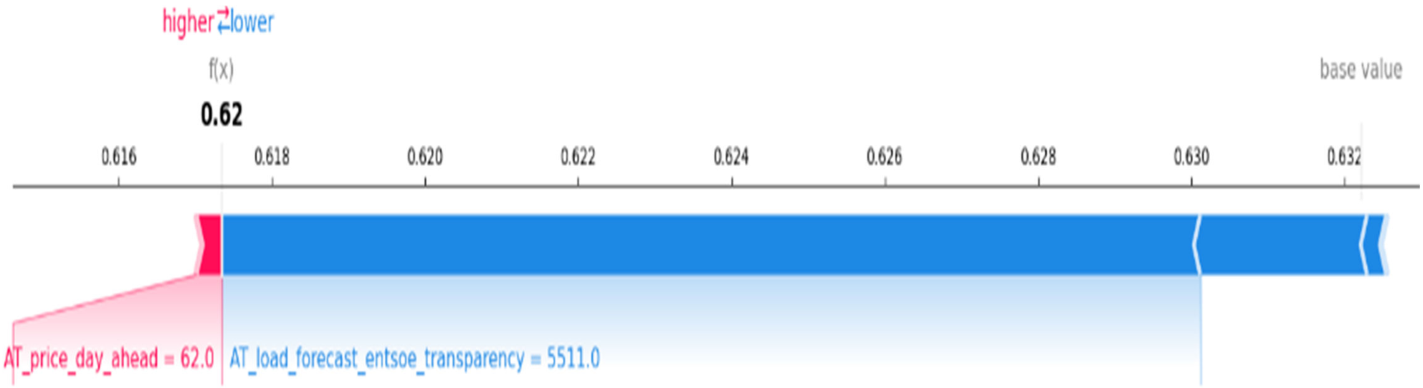

Figure 4. SHAP force plot explainability of GradientSHAP for the top features.

The SHAP waterfall plot in Figure 5 shows how each feature contributes to shifting the model's base value to reach the final prediction. Features such as ‘SE_radiation_direct_horizontal’ and “AT load forecast entsoe transparency” decrease the model's output, while ‘GB_NIR_load_forecast_entsoe_transparency’ slightly increases it. Blue bars indicate features lowering the prediction, and red bars indicate those increasing it. The plot highlights the significant impact of each feature, indicating that ‘SE_radiation_direct_horizontal’ has the strongest effect in reducing the prediction. In summary, the SHAP plot offers interpretability into the top features that influences the predictive output of the model.

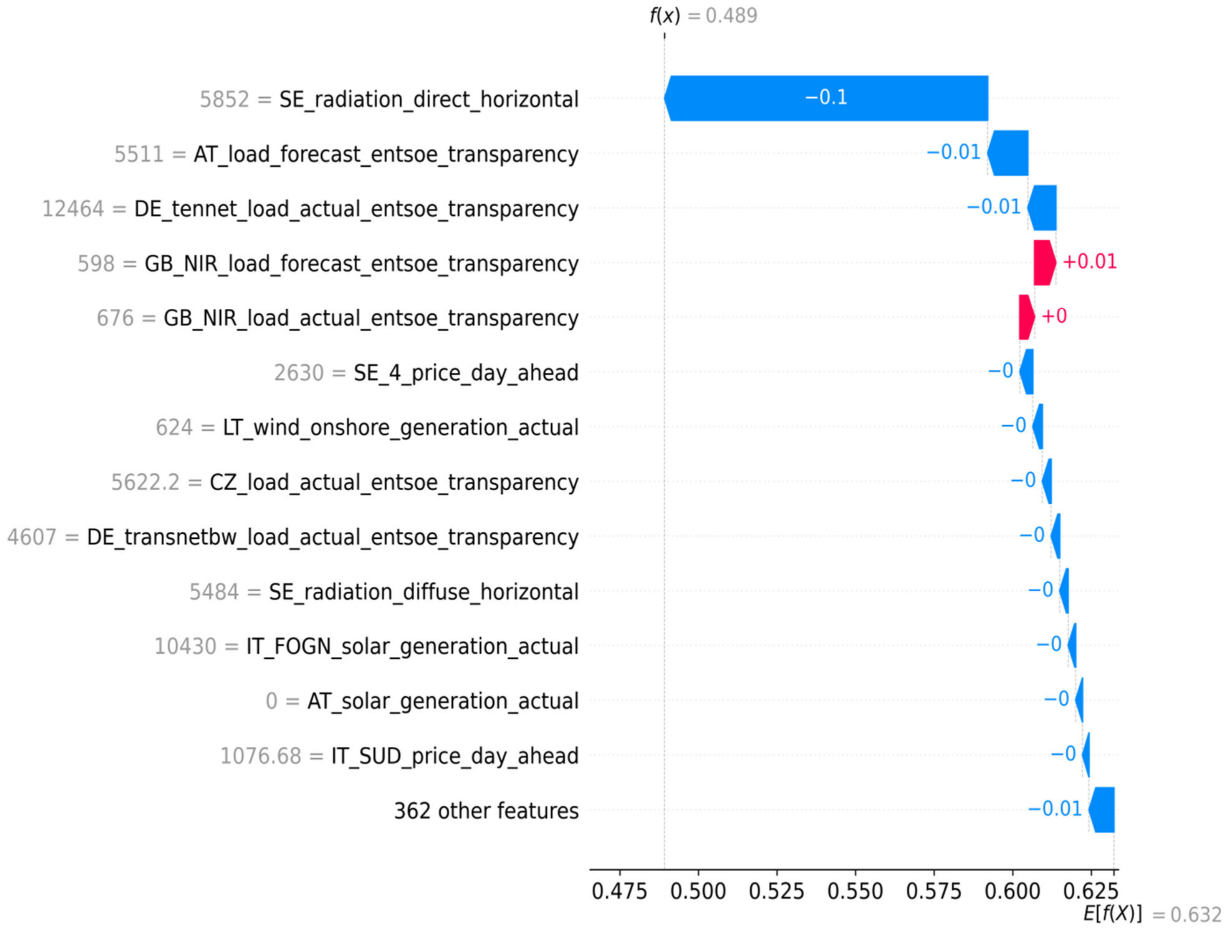

Figure 5. SHAP waterfall plot explainability of GradientSHAP for the top features.

5. CONCLUSIONS

This study proposes GradientSHAP, a methodology that combines gradient boosting with SHAP values to enhance both prediction accuracy and interpretability in electricity demand prediction. The GradientSHAP model captures complex sequence within time-series and weather data, offering a robust prediction mechanism, while the SHAP values provide intuition into the model decision-making process by emphasizing feature importance and contributions, thereby making GradientSHAP a transparent and alternative solution for energy demand prediction. Compared to LR and SVR, GradientSHAP obtained superior predictive accuracy and provides an explainable model structure for both accuracy and interpretability, while demonstrating its effectiveness in addressing challenges in predicting energy demand.

GradientSHAP demonstrates optimal predictive accuracy and interpretability, there are some drawbacks and room for improvement. Firstly, the computation of GradientSHAP can be resource-intensive, particularly with large-scale datasets, and eventually affect real-time applications. Future research direction will investigate strategies to optimize SHAP computation for scalability and efficiency. Additionally, the amalgamation of neural network algorithm with SHAP values will be investigated to further enhance prediction accuracy and interpretation across multiple data types and domains. Another area of investigation is the impact of weather indicators over long forecasting periods, considering the impact of climate change and seasonal changes on energy demand.

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