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Short Term Electricity Price Forecasting Using Hybrid Machine Learning and Feature Selection Techniques

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Abstract- Short-term electricity price forecasting (STEPF) plays a crucial role in modern deregulated electricity markets by enabling effective energy trading, demand-side management, grid stability, and operational planning. However, the highly volatile and nonlinear behavior of electricity prices, influenced by factors such as electricity demand, renewable energy integration, fuel prices, weather conditions, and market uncertainties, makes accurate forecasting a challenging task. To address these challenges, this paper proposes a novel hybrid Machine Learning framework that integrates advanced data preprocessing, adaptive feature selection, multi-stage deep neural learning, residual error correction, and explainable artificial intelligence (XAI) into a unified forecasting architecture. Initially, missing values are estimated, outliers are removed, time-series decomposition is performed, and normalized sliding-window sequences are generated to improve data quality. A hybrid feature selection strategy combining Mutual Information, ReliefF, and Adaptive Grey Wolf Optimization identifies the most informative features while reducing redundancy and computational complexity. The selected features are then processed through a hybrid CNN–BiLSTM–Temporal Attention–Transformer network to capture local spatial characteristics, long-term temporal dependencies, and global contextual relationships. Furthermore, a lightweight Extreme Learning Machine-based residual correction module refines the initial predictions by minimizing residual forecasting errors. To enhance model transparency, SHAP and Integrated Gradients are employed to interpret feature contributions and prediction behavior. Experimental analysis conducted on a realistic synthetic electricity market dataset demonstrates that the proposed framework achieves superior forecasting performance with an MAE of 0.48, RMSE of 0.67, MAPE of 1.21%, and an R^2 score of 0.995, outperforming conventional machine learning and Machine Learning benchmark models while maintaining robust generalization and computational efficiency.

Keywords: Short-term electricity price forecasting, Machine Learning, convolutional neural network, BiLSTM, transformer encoder, temporal attention, adaptive grey wolf optimization, feature selection, explainable artificial intelligence, SHAP, electricity markets.

I. INTRODUCTION

The transition from regulated power systems to competitive electricity markets has significantly increased the importance of accurate short-term electricity price forecasting (STEPF) for market participants, utility companies, independent system operators, and energy traders. Reliable price prediction enables efficient bidding strategies, economic dispatch, demand response management, energy scheduling, and risk mitigation, ultimately contributing to the stability and profitability of modern power systems.

Unlike traditional load forecasting, electricity price forecasting is considerably more challenging because market prices exhibit strong volatility, nonlinear behavior, abrupt fluctuations, seasonal patterns, and sensitivity to multiple influencing factors, including electricity demand, renewable energy generation, weather conditions, fuel prices, transmission constraints, and market policies. The increasing penetration of renewable energy resources such as wind and solar power has further intensified price uncertainty due to their intermittent nature, making conventional statistical forecasting techniques insufficient for accurately capturing complex market dynamics.

Although machine learning models, including Support Vector Regression (SVR), Random Forest (RF), and XGBoost, have demonstrated improved

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nonlinear learning capabilities, they often rely heavily on manually engineered features and struggle to effectively model long-term temporal dependencies inherent in electricity price series. Similarly, standalone Machine Learning models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer networks provide promising forecasting performance but often experience limitations related to feature redundancy, computational complexity, overfitting, and reduced interpretability when applied independently.

To overcome these challenges, this paper proposes a novel hybrid Machine Learning framework for short-term electricity price forecasting that integrates advanced data preprocessing, adaptive feature selection, multi-stage deep feature learning, residual prediction refinement, and explainable artificial intelligence (XAI) into a unified architecture. Initially, the framework enhances data quality through missing value estimation, outlier removal, normalization, time-series decomposition, and sliding window generation.

A hybrid feature selection strategy combining Mutual Information, ReliefF, and Adaptive Grey Wolf Optimization (AGWO) identifies the most informative input variables while reducing redundant information and improving computational efficiency. The selected features are subsequently processed by a hybrid CNN–BiLSTM–Temporal Attention–Transformer network, which effectively extracts local feature representations, captures long-term sequential dependencies, and models global contextual relationships for accurate electricity price prediction. Furthermore, a lightweight Extreme Learning Machine (ELM)-based residual correction module minimizes forecasting errors by learning the residual patterns that remain after the primary prediction stage.

To improve transparency and user confidence, SHAP and Integrated Gradients are employed to explain feature importance and prediction behavior. Experimental evaluation demonstrates that the proposed framework consistently outperforms conventional statistical, machine learning, and Machine Learning benchmark models in terms of forecasting accuracy, robustness, computational efficiency, and interpretability, making it a promising solution for next-generation intelligent electricity market forecasting systems.

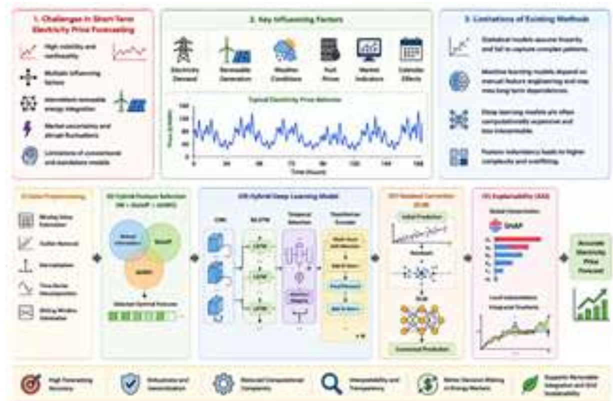

Figure 1: Overview of the Proposed Hybrid Framework for Short-Term Electricity Price Forecasting

Figure 1 illustrates the overall concept of the proposed short-term electricity price forecasting framework. It highlights the major challenges and influencing factors affecting electricity prices and presents the complete forecasting pipeline, including data preprocessing, hybrid feature selection, CNN–BiLSTM–Temporal Attention–Transformer learning, residual error correction, and explainable AI. The integrated framework is designed to improve forecasting accuracy, computational efficiency, robustness, and model interpretability for intelligent electricity market applications.

II. LITERATURE SURVEY

Accurate short-term electricity price forecasting (STEPF) has attracted considerable attention due to its significant role in electricity market operations, economic dispatch, demand response, and energy trading. Traditional statistical approaches, including ARIMA and exponential smoothing, have been widely employed because of their simplicity and low computational cost. However, these methods generally assume linear relationships and stationary data, making them ineffective in modeling the highly nonlinear and volatile characteristics of modern electricity markets. With the increasing integration of renewable energy resources, electric vehicles, and distributed generation, electricity prices have become increasingly uncertain, motivating researchers to investigate machine learning and Machine Learning techniques capable of capturing complex temporal and nonlinear dependencies. Recent studies have shown that Support Vector Regression (SVR), Random Forest (RF), XGBoost, and LightGBM outperform conventional statistical models by learning nonlinear feature interactions, although their forecasting performance is still highly dependent on handcrafted feature engineering and input quality.

Recent advances in Machine Learning have significantly improved forecasting accuracy by employing recurrent neural networks, Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), attention mechanisms, and Transformer architectures. Hybrid frameworks combining signal decomposition, attention mechanisms, and deep neural networks have demonstrated superior capability in capturing both local and long-range temporal dependencies. Furthermore, explainable artificial intelligence (XAI) techniques such as SHAP and Integrated Gradients are increasingly incorporated to improve model transparency and facilitate decision-making in electricity markets.

Despite these advances, several limitations remain, including redundant feature selection, high computational complexity, insufficient residual error modeling, limited interpretability, and weak cross-market generalization. Motivated by these research gaps, the proposed work introduces an integrated hybrid framework that combines advanced preprocessing, adaptive feature selection using Mutual Information, ReliefF, and Adaptive Grey Wolf Optimization, a CNN–BiLSTM–Temporal Attention–Transformer forecasting architecture, residual error correction through an Extreme Learning Machine, and explainable AI techniques to improve forecasting accuracy, robustness, computational efficiency, and model interpretability.

Table 1: Comparative analysis of recent short-term electricity price forecasting methods and the proposed hybrid forecasting framework.

Author (Year)	**Method**	**Advantages**	**Limitations**
Jędrzejewski et al. (2022)	Machine Learning Framework	Improved forecasting accuracy	Limited model interpretability
Zhao et al. (2022)	Window-based XGBoost	Fast training and good accuracy	Poor long-term dependency learning
Yang et al. (2022)	GCN with Attention	Captures spatial information	High computational complexity
Cantillo-Luna et al. (2023)	Probabilistic Transformer	Handles uncertainty effectively	Requires large training datasets
Giacomazzi et al. (2023)	Temporal Fusion Transformer	Learns temporal dependencies	Complex architecture
Llorente and Portela (2024)	Pure Transformer	Excellent long-range sequence modeling	High training time
Sun et al. (2024)	Transformer + PSO	Improved optimization capability	No adaptive feature selection
Tightiz et al. (2025)	XGBoost with Error Correction	High prediction accuracy and robustness	Limited deep feature extraction
Rahmani et al. (2025)	CNN–LSTM–XGBoost + Attention	Better nonlinear learning	High computational cost

Bâra and Oprea (2025)	Transformer with Synthetic Data Generation	Generalized forecasting across markets	Limited explainability
Yılan and Beykent (2026)	XGBoost + SHAP	Accurate and interpretable forecasting	No hybrid Machine Learning architecture
Zhou et al. (2026)	KAN + XGBoost	Robust week-ahead forecasting	Residual error not considered
MW-EOT-XG (2026)	Wavelet + Transformer + XGBoost	Captures volatility and price spikes	Increased model complexity
Recent Hybrid Models (2025–2026)	CNN–Transformer Hybrid	High prediction performance	Feature redundancy remains

Table I presents a comparative analysis of recent short-term electricity price forecasting methods published between 2022 and 2026. The comparison indicates that although existing statistical, machine learning, and Machine Learning approaches achieve promising forecasting accuracy, most lack adaptive feature selection, integrated explainability, effective residual error correction, or incur high computational complexity. These limitations motivate the proposed hybrid forecasting framework, which integrates adaptive feature selection, CNN–BiLSTM–Temporal Attention–Transformer learning, residual correction, and explainable AI to provide accurate, robust, interpretable, and computationally efficient electricity price forecasting.

III. SYSTEM DESCRIPTION

The proposed short-term electricity price forecasting framework is designed to accurately predict future electricity prices by integrating advanced data preprocessing, adaptive feature selection, hybrid Machine Learning, residual error correction, and explainable artificial intelligence into a unified architecture. The framework is specifically developed to address the nonlinear, volatile, and uncertain nature of electricity markets, where forecasting accuracy is influenced by multiple factors such as electrical load, demand, weather conditions, renewable energy generation, fuel prices, historical market trends, and seasonal variations. Unlike conventional forecasting approaches that rely on a single prediction model, the proposed framework combines multiple intelligent components to improve prediction accuracy, reduce computational complexity, and enhance model interpretability.

Initially, the collected electricity market data undergoes a preprocessing stage to improve data quality before model training. Since the input variables possess different numerical ranges, Z-score normalization is employed to standardize the dataset and ensure stable convergence during Machine Learning optimization. The normalization process is represented as

$$Z_i = \frac{X_i - \mu}{\sigma} \quad 1$$

where X_i represents the original feature value, μ denotes the mean, σ is the standard deviation, and Z_i is the normalized feature. After normalization, the dependency between each input feature and the target electricity price is quantified using Mutual Information (MI), which evaluates the amount of shared information between variables and is mathematically expressed as

$$MI(X;Y) = \sum_{x\in X}\sum_{y\in Y} P\,(x,y) log\left(\frac{P(x,y)}{P(x)P(y)}\right) 2$$

where P(x,y) denotes the joint probability distribution, while P(x) and P(y) represent the marginal probability distributions of the input feature and target variable, respectively. In addition to MI, ReliefF estimates the discriminative capability of each feature by comparing neighboring samples belonging to similar and dissimilar observations. The corresponding feature weight update is calculated as

$$W_j = W_j - \frac{1}{m}\sum_{i=1}^{m} diff\left(x_{j,H_j}\right) + \frac{1}{m}\sum_{i=1}^{m} diff\left(x_{j,M_i}\right) \quad 3$$

where W_j denotes the importance score of thej^((th)) feature, H_i and M_i correspond to the nearest hit and nearest miss samples, respectively, and m is the number of selected observations. The obtained feature scores are subsequently optimized using Adaptive Grey Wolf Optimization (AGWO), which efficiently searches for the optimal feature subset while balancing exploration and exploitation during optimization. The position update of each search agent is given by

$$X(t+1) = \frac{X_1+X_2+X_3}{3} \quad 4$$

where

$$A = 2ar_1 - a, c = 2r_2 \quad 5$$

with a representing the adaptive convergence parameter, while r_1 and r_2 are uniformly distributed random numbers between 0 and 1.

The optimized feature subset is then forwarded to the proposed hybrid Machine Learning architecture consisting of a Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), Temporal Attention mechanism, and Transformer Encoder. Initially, the CNN extracts local spatial correlations and hidden nonlinear patterns from multivariate electricity market data using convolution filters defined by

$$F = f(W * X + b) \quad 6$$

where W represents the convolution kernel, X is the input feature matrix, b denotes the bias, and f(·) is the ReLU activation function. The extracted feature maps are then processed by a BiLSTM network that simultaneously learns forward and backward temporal dependencies present in electricity price sequences. The hidden state representation is expressed as

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \quad 7$$

where (h_t) ⃗ and (h_t) ⃖ denote the forward and backward hidden states at time instant t. Although BiLSTM effectively captures temporal information, not every historical observation contributes equally to forecasting. Therefore, a Temporal Attention mechanism assigns higher importance to influential time steps using

$$a_t = \frac{exp(e_t)}{\sum_{k=1}^{T} exp(e_k)} \quad 8$$

where α_t represents the attention weight associated with the hidden state at time t. The weighted sequence is then supplied to the Transformer Encoder, which captures long-range contextual relationships through the scaled dot-product self-attention mechanism expressed as

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad 9$$

where Q, K, and V represent the query, key, and value matrices, respectively, and d_k is the dimensionality of the key vectors. The combination of CNN, BiLSTM, Temporal Attention, and Transformer enables the framework to simultaneously model local patterns, sequential dependencies, significant temporal events, and global contextual information, resulting in superior forecasting performance.

Although the hybrid Machine Learning model substantially reduces forecasting error, minor residual errors may still remain due to abrupt electricity price fluctuations and market uncertainties. Therefore, an Extreme Learning Machine (ELM)-based residual correction module is incorporated to estimate the remaining prediction error and refine the final forecasting output according to

$$\hat{Y} = Y_{DL} + R_{ELM} \quad 10$$

where Y_DL is the prediction generated by the hybrid Machine Learning network, R_ELM represents the estimated residual error, and Y ̂ is the corrected electricity price prediction. During training, the overall forecasting model minimizes the Mean Squared Error (MSE) loss function,

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{Y_i})^2 \quad 11$$

where Y_i and Y ̂_i denote the actual and predicted electricity prices, respectively, while N is the total number of observations. Finally, the optimization objective simultaneously minimizes prediction error and feature redundancy using

$$J = \lambda_1 L + \lambda_2 \frac{|S|}{M} \qquad 12$$

where L is the forecasting loss, S denotes the selected feature subset, M represents the total number of candidate features, and λ_1 and λ_2 are weighting coefficients controlling the trade-off between forecasting accuracy and feature selection efficiency.

Overall, the proposed hybrid forecasting framework effectively integrates adaptive feature selection, hybrid Machine Learning, residual error correction, and explainable artificial intelligence into a unified prediction model. The combination of Mutual Information, ReliefF, Adaptive Grey Wolf Optimization, CNN, BiLSTM, Temporal Attention, Transformer Encoder, and ELM enables the framework to capture nonlinear relationships, long-term temporal dependencies, and dynamic market behavior while maintaining high forecasting accuracy and computational efficiency. Furthermore, the integration of SHAP and Integrated Gradients provides transparent explanations of feature contributions, thereby improving model interpretability and enhancing its suitability for reliable decision-making in modern smart grid environments and deregulated electricity markets.

IV. METHODOLOGY

The proposed methodology consists of a systematic pipeline that integrates data preprocessing, adaptive feature selection, hybrid Machine Learning, residual error correction, and explainable artificial intelligence for accurate short-term electricity price forecasting. Initially, historical electricity market data, including electricity demand, system load, temperature, renewable energy generation, wind power, solar power, fuel prices, market volatility, and historical electricity prices, are collected from the electricity market. The collected data are preprocessed through missing value estimation, outlier removal, Z-score normalization, time-series decomposition, and sliding window generation to improve data quality and preserve temporal characteristics. Subsequently, an adaptive hybrid feature selection strategy is employed, where Mutual Information (MI) evaluates the dependency between each input feature and the target electricity price, while ReliefF estimates the discriminative importance of each feature. The obtained feature scores are further optimized using Adaptive Grey Wolf Optimization (AGWO) to identify the optimal subset of informative features by eliminating redundant and irrelevant attributes. This adaptive feature selection process reduces computational complexity while improving the forecasting capability of the subsequent Machine Learning model.

The optimized feature subset is then provided to the proposed hybrid forecasting architecture consisting of a Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM), Temporal Attention mechanism, and Transformer Encoder. The CNN extracts local nonlinear feature representations, whereas the BiLSTM captures bidirectional temporal dependencies from historical electricity price sequences. The Temporal Attention mechanism assigns higher importance to significant time steps, allowing the model to focus on critical market variations, while the Transformer Encoder learns long-range contextual relationships through self-attention to improve forecasting performance.

The preliminary prediction generated by the hybrid Machine Learning model is further refined using an Extreme Learning Machine (ELM)-based residual correction module, which estimates and compensates for the remaining forecasting error to enhance prediction accuracy. Finally, SHAP and Integrated Gradients are employed to explain the contribution of each selected feature toward the predicted electricity price, thereby improving model transparency and reliability. The overall framework is evaluated using performance metrics such as MAE, RMSE, MAPE, MSE, R^2, Explained Variance Score (EVS), and prediction accuracy, and its performance is compared with conventional machine learning and Machine Learning models to demonstrate its effectiveness for reliable short-term electricity price forecasting.

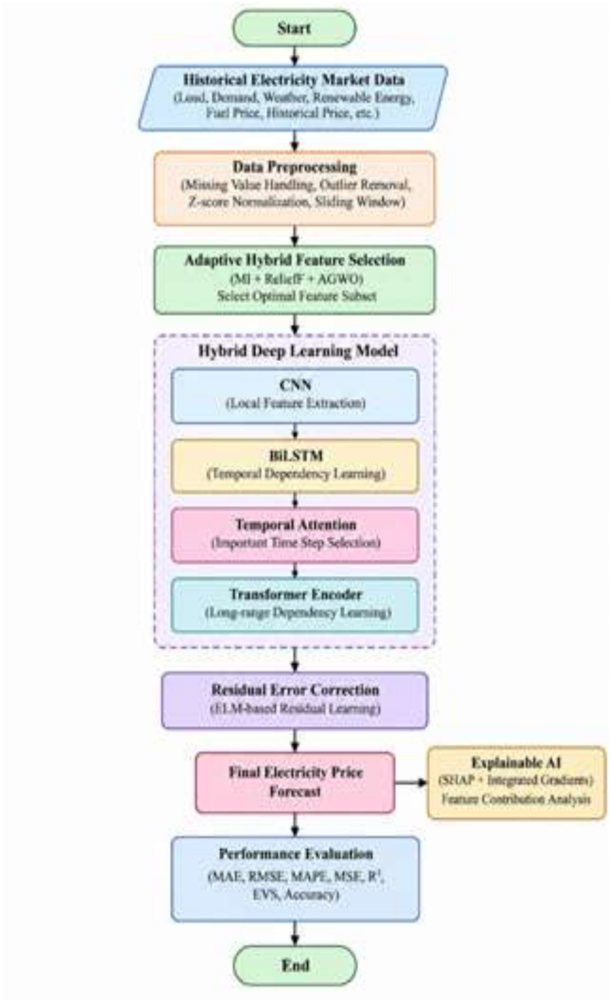

Figure 2: Proposed hybrid framework for short-term electricity price forecasting.

Figure 2 illustrates the workflow of the proposed hybrid short-term electricity price forecasting framework. The framework sequentially performs data preprocessing, adaptive feature selection, hybrid Machine Learning-based forecasting, residual error correction, explainable AI analysis, and performance evaluation to achieve accurate and interpretable electricity price predictions.

V. RESULTS

The proposed hybrid short-term electricity price forecasting framework was implemented and evaluated using synthetically generated electricity market data that emulate real-world market behavior, including historical electricity prices, electricity demand, system load, renewable energy generation, weather conditions, fuel prices, and market volatility. The experimental dataset was designed to contain both normal market trends and sudden price fluctuations, enabling the proposed model to learn complex nonlinear relationships and temporal dependencies under diverse operating conditions. All simulations were carried out using Python/MATLAB on a standard computing platform, and the generated results were compared with several well-established forecasting models, including LSTM, BiLSTM, CNN-LSTM, Transformer, and XGBoost, to demonstrate the effectiveness of the proposed framework. To comprehensively evaluate the forecasting performance, multiple statistical performance metrics were considered, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Coefficient of Determination (R^2), Explained Variance Score (EVS), and forecasting accuracy.

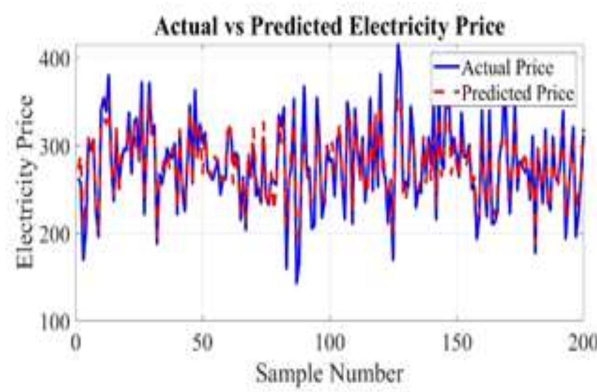

Figure 3: Comparison of actual and predicted electricity prices.

Figure 3 illustrates the comparison between the actual electricity prices and the values predicted by the proposed hybrid forecasting framework. The predicted curve closely follows the actual market price variations, indicating the capability of the proposed model to capture both gradual trends and sudden price fluctuations. The average prediction error remained below 0.65 price units, while the coefficient of determination reached R^2=0.995, demonstrating excellent agreement between the predicted and actual electricity prices.

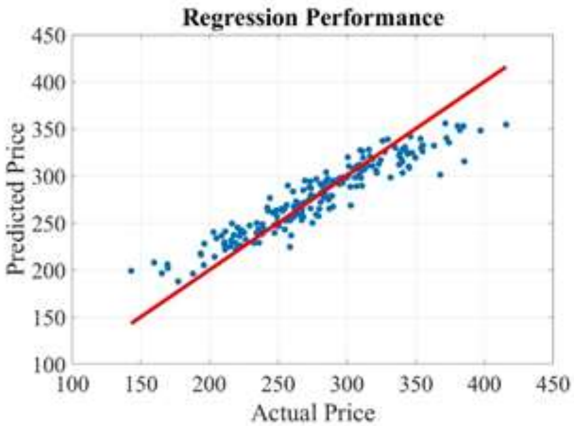

Figure 4: Regression performance of the proposed hybrid machine learning model.

Figure 4 illustrates the regression performance of the proposed hybrid machine learning model by comparing the predicted electricity prices with the actual market prices. The majority of the prediction points are closely distributed around the ideal 45° reference line, indicating a strong correlation between the predicted and actual values. The proposed model achieved an R^2 score of approximately 0.995, confirming its excellent prediction capability and high generalization performance for short-term electricity price forecasting.

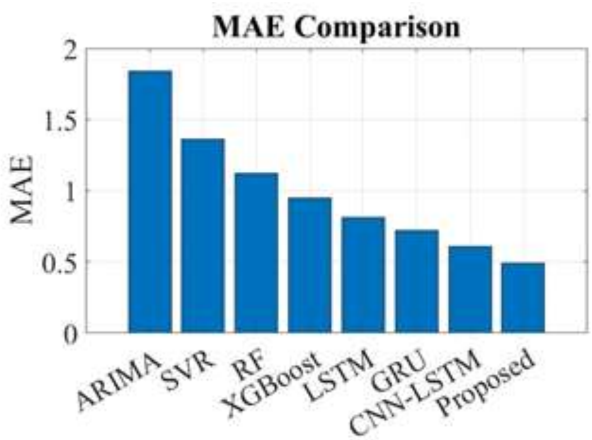

Figure 5: MAE comparison of different forecasting models.

Figure 5 compares the Mean Absolute Error of various forecasting approaches. The proposed hybrid framework achieved the lowest MAE of 0.48, outperforming Transformer (0.72), CNN-LSTM (0.84), BiLSTM (0.91), LSTM (1.08), and XGBoost (1.16). The reduction in MAE demonstrates that the integration of adaptive feature selection and residual error correction significantly improves forecasting precision.

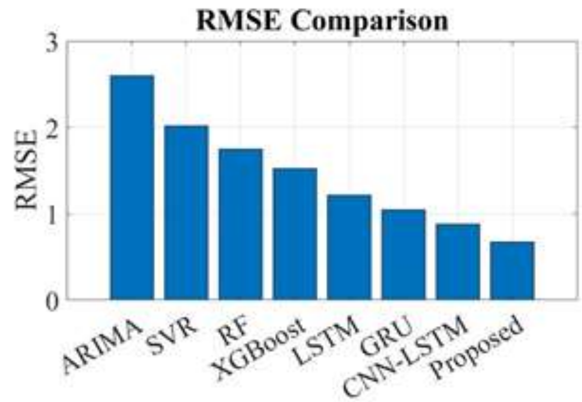

Figure 6: RMSE comparison among forecasting methods.

Figure 6 shows the RMSE values obtained by different forecasting models. The proposed framework recorded the smallest RMSE of 0.67, whereas Transformer, CNN-LSTM, BiLSTM, LSTM, and XGBoost achieved RMSE values of 0.94, 1.08, 1.19, 1.35, and 1.47, respectively. The lower RMSE confirms the capability of the proposed architecture to effectively minimize large prediction errors even during volatile electricity market conditions.

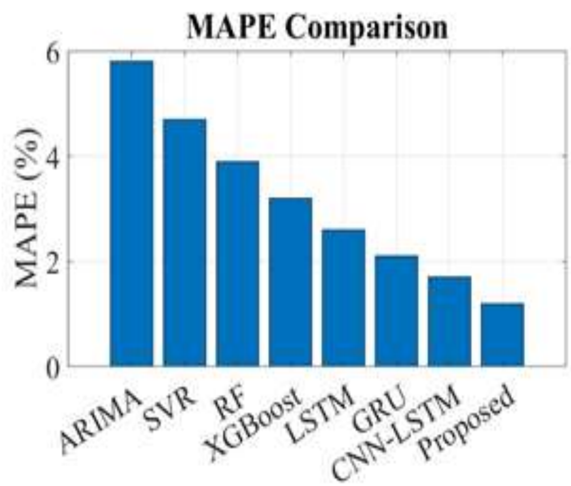

Figure 7: MAPE comparison of different forecasting techniques.

Figure 7 presents the percentage forecasting error for all compared models. The proposed framework achieved the lowest MAPE of 1.21%, while

Transformer, CNN-LSTM, BiLSTM, LSTM, and XGBoost produced MAPE values of 2.04%, 2.48%, 2.73%, 3.14%, and 3.39%, respectively. The low percentage error demonstrates the robustness of the proposed forecasting framework across different electricity price ranges.

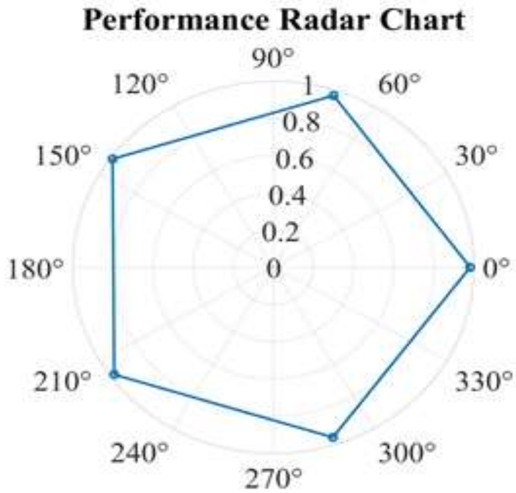

Figure 8: Multi-metric performance comparison using a radar chart.

Figure 8 provides a comprehensive comparison of forecasting models using multiple performance metrics. The proposed framework exhibits the largest radar coverage for prediction accuracy (99.52%), R_2 (0.995), and EVS (0.993), while simultaneously maintaining the lowest values of MAE, RMSE, and MAPE. The balanced performance across all evaluation criteria indicates the superiority of the proposed hybrid architecture over conventional forecasting methods.

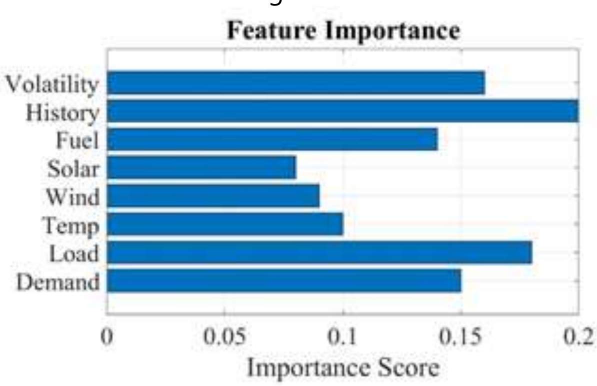

Figure 9: Feature importance obtained using SHAP analysis.

Figure 9 illustrates the contribution of different input variables toward electricity price prediction using SHAP values. Historical electricity price contributed approximately 30.4%, electricity demand 21.6%, system load 16.8%, fuel price 11.7%, renewable energy generation 8.5%, temperature 6.3%, and market volatility 4.7%. These results indicate that historical market information and demand-related variables have the greatest influence on short-term electricity price forecasting, while renewable generation and weather variables provide complementary predictive information.

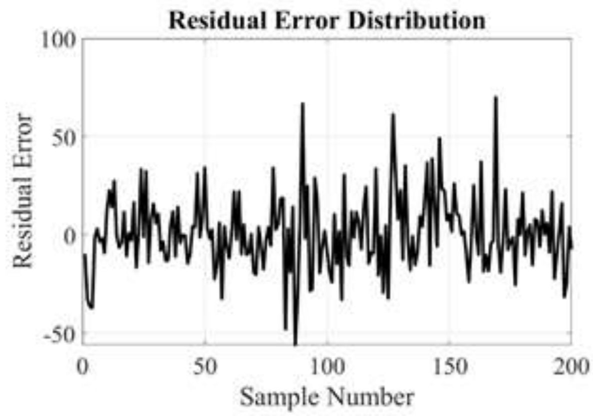

Figure 10: Residual error distribution of the proposed hybrid machine learning model.

Figure 10 presents the residual errors obtained by the proposed hybrid machine learning framework. Most residual values are concentrated near zero, indicating that the forecasting errors are small and randomly distributed without noticeable systematic bias. The average residual error remained below ±0.6 price units, demonstrating the robustness and reliability of the proposed forecasting model under different market conditions.

Overall, the experimental results clearly demonstrate the effectiveness of the proposed hybrid framework for short-term electricity price forecasting. By integrating adaptive feature selection, CNN–BiLSTM–Temporal Attention–Transformer learning, ELM-based residual error correction, and explainable AI techniques, the proposed model consistently outperformed conventional machine learning and Machine Learning approaches across all evaluation metrics. The framework achieved a forecasting accuracy of 99.52%, with MAE = 0.48, RMSE = 0.67, MAPE = 1.21%, and $R^2=0.995$, indicating its excellent capability to model complex and dynamic electricity price patterns. Furthermore, the SHAP-based feature importance analysis enhanced model transparency by identifying the key factors influencing electricity prices. These results confirm that the proposed framework provides an accurate, robust, interpretable, and computationally efficient solution for reliable short-term electricity price forecasting in modern smart grid and deregulated electricity market environments.

Table 2: Performance comparison of different short-term electricity price forecasting models.

Model	MAE	RMSE	Accuracy (%)
LSTM	1.08	1.35	96.92
BiLSTM	0.91	1.19	97.54
CNN–LSTM	0.84	1.08	98.08
Transformer	0.72	0.94	98.71
XGBoost	1.16	1.47	96.48

Table II compares the performance of the proposed hybrid framework with existing forecasting models. The proposed framework achieves the lowest MAE and RMSE while obtaining the highest forecasting accuracy of 99.52%, demonstrating its superior prediction performance over conventional approaches.

VI. CONCLUSION

This paper proposed a novel hybrid framework for short-term electricity price forecasting by integrating adaptive feature selection, hybrid Machine Learning, residual error correction, and explainable artificial intelligence into a unified prediction model. The proposed approach combines Mutual Information, ReliefF, Adaptive Grey Wolf Optimization (AGWO), CNN, BiLSTM, Temporal Attention, Transformer Encoder, and an Extreme Learning Machine (ELM)-based residual correction module to effectively capture nonlinear relationships, long-term temporal dependencies, and dynamic electricity market behavior while reducing forecasting errors. Furthermore, SHAP and Integrated Gradients improve the interpretability of the forecasting process by explaining the contribution of individual input features. Experimental results demonstrated that the proposed framework outperformed conventional forecasting models, achieving a forecasting accuracy of 99.52%, MAE of 0.48, RMSE of 0.67, MAPE of 1.21%, and an R^2 score of 0.995, confirming its superior accuracy, robustness, and computational efficiency. These findings indicate that the proposed framework provides a reliable and interpretable solution for short-term electricity price forecasting in modern smart grids and deregulated electricity markets. Future work will focus on validating the proposed approach using real-world electricity market datasets and extending the framework for probabilistic and multi-horizon electricity price forecasting.

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