Electricity Market Time-of-use Price Fluctuation Trend Prediction Based On CEEMDAN And Bidirectional GRU

Jie Han[1*], Shiqi Tang[1], Peng Wang[2], and Zheng Yao[3]

[1] China Mobile (Shanghai) Information Communication Technology Co.,Ltd, Shanghai, 2002131, China
[2] China Datang Corporation Limited Zhejiang Branch, Hangzhou, Zhejiang, 310016, China
[3] Zhejiang Datang Energy Marketing Co.,Ltd, Hangzhou, Zhejiang, 310016, China
[*] Corresponding author. E-mail: Jie_Han111@outlook.com

Received: Apr. 01, 2026; Accepted: Apr. 28, 2026

Electricity market price forecasting plays a vital role in power system dispatch and energy management. However, accurate forecasting is challenging due to the non-stationarity, multi-scale volatility, and complex nonlinear characteristics of electricity price data. This study presents a CEEMDAN-BiGRU-based approach to address these challenges. The method first decomposes the electricity price sequence into multiple intrinsic mode functions (IMFs) using complete ensemble empirical mode decomposition (CEEMDAN), which captures features across different time scales and mitigates non-stationarity. A bidirectional gated recurrent unit (BiGRU) is then used for time-series modeling of each component, capturing both forward and backward time dependencies. The individual forecasts of each component are reconstructed to provide the final forecast. Experimental results across various electricity market datasets show that the proposed method outperforms comparative models in terms of RMSE, MAE, MAPE, and trend accuracy, demonstrating robust performance and generalization across different seasons and time periods.

Keywords: Electricity price forecasting; CEEMDAN; BiGRU; multi-scale modeling; non-stationary time series; electricity market

http://dx.doi.org/10.6180/jase.202610_33.041

1. Introduction

With ongoing power market reforms and the integration of renewable energy, the operating environment for the power system is becoming more complex and dynamic [1]. Electricity prices are increasingly volatile, exhibiting non-stationarity, multi-scale volatility, and high uncertainty, making accurate forecasting essential for optimizing dispatch strategies and supporting power trading and demand response [2]. Non-stationarity refers to time-varying statistical properties, while volatility involves rapid price fluctuations, complicating forecasting for models like ARIMA, which assumes stationarity and linearity. Models such as CEEMDAN combined with BiGRU are better suited for capturing these challenges [3]. Electricity price data shows significant non-stationarity and multi-scale fluctuations, influenced by external factors like load demand and weather conditions, which complicates modeling [4, 5]. Early forecasting methods like ARIMA and machine learning models such as Support Vector Regression (SVR) have limitations in handling non-linear and non-stationary data. Recent deep learning methods, including RNNs, LSTM, and GRUs, have improved forecasting but still struggle with multi-scale fluctuations and non-stationarity [6–9]. This paper proposes a CEEMDAN-BiGRU-based method, using CEEMDAN for multi-scale decomposition of electricity price data and BiGRU to capture both past and future dependencies. The final forecast is obtained by fusing and reconstructing the prediction results of each component, providing improved accuracy and robustness in electricity price forecasting.

2. Theory and formula

2.1. Literature

2.1.1. Overall Framework

BiGRU processes data bidirectionally, capturing both past and future dependencies, making it more effective for forecasting electricity prices compared to unidirectional GRU. Prophet extracts low-frequency trends and cycles, while CEEMDAN captures high-frequency components, which are then fused for BiGRU to capture temporal dependencies across different time scales. CEEMDAN's adaptive noise mechanism improves mode separation, and a systematic criterion optimizes the number of IMFs, enhancing forecasting accuracy and handling both long-term trends and short-term variability. Unlike ARIMA, this approach better handles non-stationarity and volatility. CEEMDAN optimizes decomposition stability by adjusting adaptive noise amplitude, and the combined features enhance BiGRU's ability to model both long-term trends and short-term fluctuations, improving forecasting accuracy. In the Prophet module, given the original time series $x(t)$, it is represented as a superposition of trend, period, and residual terms:

$$x(t) = g(t) + s(t) + r(t) \tag{1}$$

Where $g(t)$ represents the long-term trend, $s(t)$ represents the periodic fluctuation component, and $r(t)$ represents the unexplained residual term. To further model this complex dynamic, this paper introduces the CEEMDAN method to decompose the residual:

$$r(t) = \sum_{k=1}^{K} \mathrm{IMF}_k(t) + \varepsilon(t) \tag{2}$$

Where $\mathrm{IMF}_k(t)$ represents the K th intrinsic mode function, and $\varepsilon(t)$ is the final residual. CEEMDAN effectively avoids mode aliasing by introducing adaptive noise and performing

ensemble averaging, enabling each IMF to correspond to oscillation modes within different frequency ranges. Its decomposition process can be expressed as:

$$r_1(t) = r(t) - \mathrm{IMF}_1(t) \tag{3}$$

$$\mathrm{IMF}\, k(t) = \frac{1}{N} \sum i = 1^N E_1\left(r_{k-1}(t) + \epsilon_{k-1} E_{k-1}\left(w_i(t)\right)\right) \tag{4}$$

By recursively extracting multi-scale components layer by layer, the original complex sequence is decomposed into multiple relatively stable subsequences, thereby reducing the modeling difficulty. Within a history window of length (T), the input matrix can be represented as:

$$\boldsymbol{X}_t = \left[\boldsymbol{x}_{t-T+1}, \boldsymbol{x}_{t-T+2}, \ldots, \boldsymbol{x}_t\right]^\top \in \mathbb{R}^{T\times(K+F)} \tag{5}$$

Where K represents the number of IMF components and F represents the structural feature dimension. This input represents the simultaneous integration of low-frequency trend information and high-frequency fluctuation features, transforming the original non-stationary sequence into a feature space with a clear structural hierarchy. The outputs from CEEMDAN (IMFs) and Prophet features (trend, daily/weekly cycles) are concatenated into a unified input matrix for BiGRU, ensuring dimensional consistency and allowing the model to learn both low- and high-frequency patterns efficiently.

2.2. BiGRU-Based Temporal Modeling

As shown in Fig. 1, the paper introduces a bidirectional recurrent neural network (BiGRU) to model dynamic dependencies in time series. Since power time series are influenced by both historical states and potential future trends, a unidirectional recurrent structure is insufficient for capturing full time dependency information [10, 11]. The BiGRU is used as the core modeling structure, combined with batch normalization and a parameterized activation function (PReLU) to ensure stable and efficient time series prediction. Dropout and gradient clipping are incorporated into the training process to stabilize learning, mitigating volatility and preventing overfitting while controlling large gradient updates for more stable performance.

Dimensionality reduction techniques, such as PCA or feature selection, are applied to control feature redundancy, retaining only the most relevant features for the BiGRU model, thus improving efficiency and preventing overfitting.

A sensitivity analysis shows that Leaky ReLU's fixed slope limits flexibility for non-stationary data, while PReLU's learnable α improves stability and performance, especially during price spikes. BiGRU uses update and reset gates to control information flow, addressing the vanishing gradient problem and enhancing long-term dependency learning. ProSparse attention reduces computational complexity by selecting significant query-key pairs, preserving key information for accurate predictions. The BiGRU architecture consists of two layers with 128 hidden units, using ReLU for hidden layers and a linear activation for the output, ensuring effective temporal dependency learning.

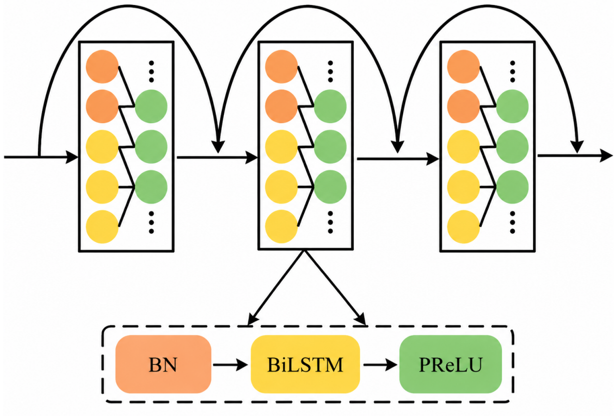

Fig. 1. Architecture of the BiGRU-based temporal modeling

2.3. Encoder-Decoder with ProSparse Attention

2.3.1. Encoder Structure

The encoder takes the concatenated feature representation as input and extracts key dependencies through multi-layer ProSparse self-attention modules [12]. The "important subset of queries" is selected based on attention weights, with a threshold determining which queries exceed the significance level. The sparsity factor is adjusted based on sequence length during training, ensuring efficient processing. ProSparse attention is chosen over other mechanisms due to its computational efficiency and effectiveness in handling long-sequence forecasting tasks, offering a scalable solution for large sequences without sacrificing accuracy.

2.3.2. Decoder Structure

During the testing phase, the decoder receives a portion of the historical input and a placeholder sequence (as shown by the " 0 " padding in the figure), and gradually generates prediction results using a masking mechanism. Its core lies in modeling future sequences through the combined effect of self-attention and cross-attention.

3. Results and discussion

3.1. Datasets and Experimental Settings

To evaluate the effectiveness and generalization of the proposed model, several publicly available electricity market datasets are used, including PJM (USA), Nord Pool (Nordic), and EPEX (European) markets [13]. The data is divided chronologically into training (70%), validation (10%), and test (20%) sets to prevent information leakage. The data is uniformly set to an hourly resolution, with missing values filled using linear interpolation. Load demand and meteorological factors, such as temperature and humidity, are included as input features to better capture external influences on electricity price fluctuations.

3.2. Baseline Models

1. ARIMA: A classic time series model used to model linear dependencies.
2. SVR: Support Vector Regression model, suitable for nonlinear prediction.
3. LSTM: Long Short-Term Memory network, used to model time dependencies.
4. GRU: Gated Recurrent Unit, with fewer parameters and faster convergence.
5. BiLSTM: Bidirectional LSTM, enhancing the ability to model temporal context.
6. Transformer: A sequence modeling method based on self-attention mechanism.
7. CEEMDAN-LSTM: A decomposition-prediction framework, validating the effectiveness of the decomposition method [14].
8. CEEMDAN-BiGRU: The closest comparison method to the structure presented in this paper (with the enhancement modules removed) [15].

3.3. Experimental Results

To comprehensively evaluate the performance of the proposed method, this paper conducts systematic experiments on multiple real-world electricity market datasets and compares it with various baseline methods. The experimental results are shown in Tables 1 to 3.

As shown in Table 1, the proposed model achieves optimal performance across all evaluation metrics on the PJM dataset. Compared to traditional statistical models (ARIMA, SVR), deep learning models (LSTM, GRU) significantly reduce prediction errors, highlighting the need for neural networks to model the nonlinear characteristics in electricity price data. However, a single deep learning model is insufficient to fully capture the multi-scale fluctuation structure of electricity prices.

The introduction of CEEMDAN decomposition (CEEMDAN-LSTM, CEEMDAN-BiGRU) improves model performance by addressing non-stationarity. The proposed method integrates Prophet's trend and periodic features with CEEMDAN-BiGRU and adds an attention mechanism, achieving optimal results. The model reduces RMSE and MAE by 8.7% and 10.5%, respectively, compared to CEEMDAN-BiGRU, while improving trend accuracy (TA)

Table 1. Prediction performance comparison on the PJM dataset

Model	RMSE	MAE	MAPE (%)	TA
ARIMA	12.84	9.76	18.32	0.61
SVR	11.92	8.85	16.47	0.64
LSTM	9.63	7.42	13.85	0.68
GRU	9.21	7.08	13.12	0.69
BiLSTM	8.74	6.81	12.45	0.71
Transformer	8.52	6.67	12.08	0.72
CEEMDAN-LSTM	7.91	6.05	11.23	0.74
CEEMDAN-BiGRU	7.54	5.82	10.96	0.75
Proposed	**6.88**	**5.21**	**9.84**	**0.81**

to 0.81 . CEEMDAN reduces mode aliasing, effectively capturing high-frequency fluctuations without distorting low-frequency trends, and handling price spikes in electricity data.

Table 2 shows the predictive performance on the Nord Pool dataset, where increased model complexity improves performance. The Nord Pool data, with stronger volatility and regional variability, challenges generalization. Traditional models lag behind deep learning models, while CEEMDAN-based models excel due to their adaptability to multi-scale decomposition. The proposed method outperforms others, reducing RMSE by 10.3% and MAE by 8.1% compared to CEEMDAN-BiGRU, and achieving a TA score of 0.80 , demonstrating its ability to consistently capture price fluctuations in complex market environments.

Table 3 shows the experimental results on the EPEX dataset, where pronounced price spikes require stronger extremum modeling capabilities. Attention-based models like Transformer outperform traditional RNN models, emphasizing the importance of long-range dependencies. However, the proposed method, combining CEEMDAN decomposition with an attention mechanism, not only captures long-range dependencies but also improves modeling of local fluctuations. The model reduces RMSE by 19.7% and MAE by 20.4% compared to Transformer, achieving the highest trend accuracy (TA) score of 0.82 .

Table 4 shows the ablation experiment results, highlighting the importance of each module in the model's performance. Removing CEEMDAN caused a 21.2% increase in RMSE, emphasizing its crucial role in multi-scale decomposition for non-stationary data. Removing Prophet weakened long-term trend modeling, leading to higher prediction errors. Replacing BiGRU with a unidirectional GRU decreased performance, illustrating the importance of bidirectional modeling for capturing temporal dependencies. Removing the attention mechanism also degraded performance, underlining its significance in feature weighting for multi-scale information fusion.

Fig. 2 compares the actual electricity price series with the predicted results of the proposed model. The predicted curve aligns closely with the long-term trend of actual prices, demonstrating strong trend modeling capabilities, primarily due to the Prophet module's extraction of low-frequency trends. The model also effectively tracks local fluctuations, particularly during sharp price changes after 2021, highlighting the importance of CEEMDAN decomposition and BiGRU in capturing multi-scale dynamics.

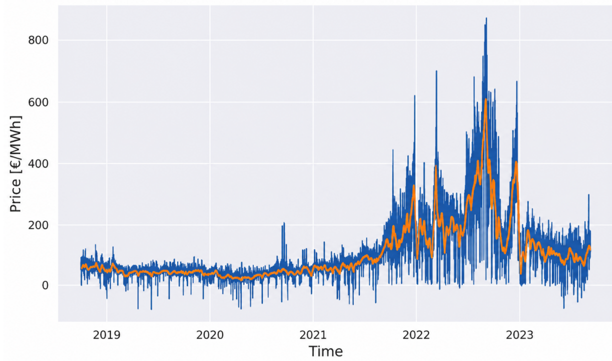

Fig. 2. Comparison between actual electricity prices and predicted results

Fig. 3 presents the results of multi-scale decomposition of the electricity price sequence using the CEEMDAN method. The decomposition separates the original signal into multiple intrinsic mode functions (IMF1-IMF8) and residual components, with higher-order components capturing high-frequency fluctuations and noise, intermediate components modeling mid-frequency fluctuations, and lower-order components reflecting long-term trends.

Fig. 4 displays the prediction results for each intrinsic mode function (IMF0-IMF8) and the final reconstructed electricity price sequence using the CEEMDAN-BiGRU framework. The model accurately captures dynamic characteristics at different frequency levels, with strong performance in long-term trend modeling (low-frequency components), mesoscale dynamic modeling (mid-frequency components), and handling high-frequency fluctuations

Table 2. Prediction performance comparison on the Nord Pool dataset

Model	RMSE	MAE	MAPE (%)	TA
ARIMA	10.37	7.88	16.05	0.60
SVR	9.94	7.41	15.12	0.63
LSTM	8.26	6.35	12.74	0.67
GRU	8.01	6.18	12.31	0.68
BiLSTM	7.63	5.91	11.89	0.70
Transformer	7.48	5.82	11.55	0.71
CEEMDAN-LSTM	6.94	5.33	10.72	0.73
CEEMDAN-BiGRU	6.71	5.18	10.41	0.75
Proposed	6.02	4.76	9.35	0.80

Table 3. Prediction performance comparison on the EPEX dataset

Model	RMSE	MAE	MAPE (%)	TA
ARIMA	11.45	8.97	17.12	0.62
SVR	10.88	8.31	16.04	0.64
LSTM	9.14	7.02	13.55	0.69
GRU	8.89	6.84	13.21	0.70
BiLSTM	8.43	6.55	12.76	0.72
Transformer	8.21	6.43	12.34	0.73
CEEMDAN-LSTM	7.65	5.98	11.48	0.75
CEEMDAN-BiGRU	7.31	5.76	11.12	0.76
Proposed	6.59	5.12	10.03	0.82

Table 4. Ablation study on PJM dataset

Variant	RMSE	MAE	TA
w/o Prophet	7.89	6.11	0.74
w/o CEEMDAN	8.34	6.48	0.72
w/o BiGRU	7.96	6.23	0.73
w/o Attention	7.42	5.74	0.77
Full Model	6.88	5.21	0.81

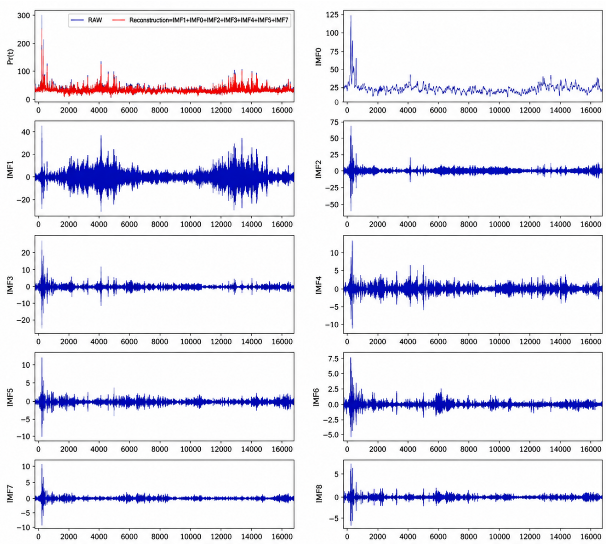

Fig. 3. CEEMDAN decomposition of the electricity price series into multiple IMFs and reconstructed signal

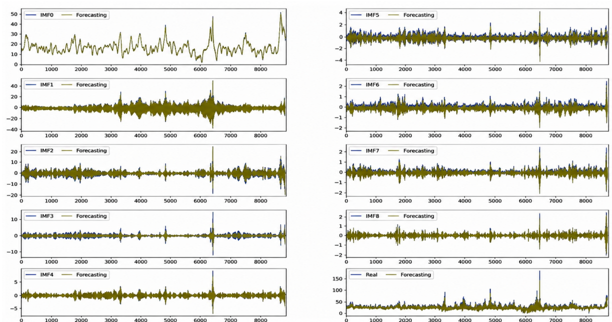

Fig. 4. Prediction performance on individual CEEMDAN components and reconstructed electricity price series

(highfrequency components). The final predicted sequence aligns well with the actual values, especially in capturing price trends, although some deviations occur during extreme events, reflecting the uncertainty in predicting price spikes.

Fig. 5 shows the distribution characteristics of electricity prices over a 24 -hour period, revealing clear intraday pe-

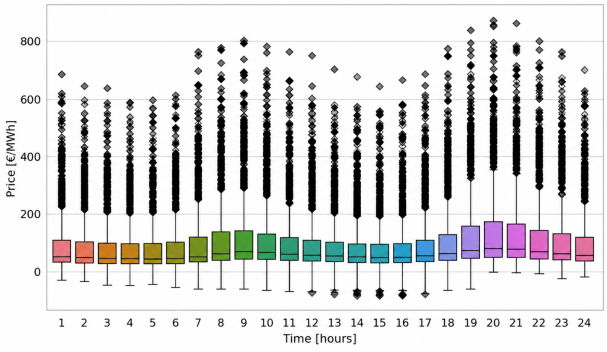

Fig. 5. Boxplot of electricity prices across 24 hours

riodicity and uneven volatility. Prices increase from early morning to noon, reflecting higher load demand, with significant price spikes and volatility during the evening peak (6-9 pm). The early morning period sees more stable, low prices. The presence of numerous outliers, particularly during peak hours, indicates a heavy-tailed, non-Gaussian distribution, complicating forecasting.

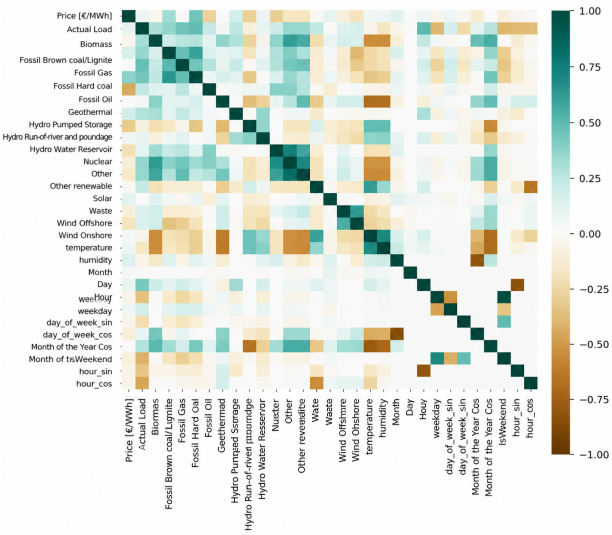

Fig. 6. Correlation heatmap of electricity price and multi-source features

Fig. 6 shows the correlation between electricity prices and factors like load, power generation methods, meteorological conditions, and temporal characteristics. Prices are strongly correlated with load, reflecting demand's impact on fluctuations. Fossil fuels correlate highly with prices, while renewable energy sources show weaker or negative correlations due to low marginal cost. Meteorological factors influence prices through load demand, and temporal characteristics exhibit periodicity.

Fig. 7 shows the joint distribution between electricity

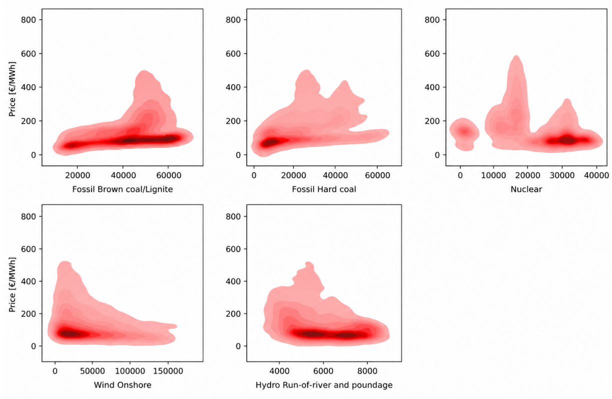

Fig. 7. Joint distribution between electricity price and key generation features

prices and key power generation characteristics, revealing a nonlinear relationship that simple linear models cannot fully capture. Fossil fuels like lignite and hard coal show a strong positive correlation with prices, especially at high output levels, while renewable sources like wind power exhibit a negative correlation, with higher wind output lowering prices.

4. Conclusion

This paper proposes a CEEMDAN-BiGRU-based method to address the challenges of nonstationarity, multi-scale fluctuations, and complex coupling in electricity price forecasting. The method decomposes the price data using CEEMDAN, mitigating non-stationarity, and uses BiGRU to capture both forward and backward time dependencies. The final forecast is generated by reconstructing component-level predictions. Experimental results show that the proposed method outperforms traditional and deep learning models in accuracy, particularly for high-volatility data. Ablation studies confirm the importance of multi-scale decomposition and bidirectional modeling in enhancing performance. The approach effectively handles nonlinearity and distribution drift, providing robust predictions across different market conditions.

5. Acknowledgements

The authors declare that this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors would like to express their sincere gratitude to all individuals and institutions who provided valuable support and guidance during the course of this study.

6. Declarations

Data Availability: Not applicable.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Funding Statement: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author Contribution:

Jie Han: Conceptualized the study, designed the research framework, and supervised the overall project. She also contributed to methodology development and manuscript review.

Shiqi Tang: Conducted data collection, performed data analysis using CEEMDAN and bidirectional GRU models, and drafted the original manuscript.

Peng Wang: Contributed to data preprocessing, model validation, and provided technical support for the implementation of the prediction algorithms.

Zheng Yao: Assisted in result interpretation, visualization, and manuscript editing, and provided domain expertise in electricity market analysis.

All authors reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Ethical Approval: This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent to Participate: Not applicable.

Consent to Publication: All authors have provided consent for publication of this manuscript.

Competing Interests: The authors declare no competing interests.

References

[1] Z. Li et al., (2026) *"Hybrid Framework for Wind Power Forecasting and Peer-to-Peer Energy Trading to Enhance Grid Stability and Market Efficiency"* **Smart Grids and Sustainable Energy *11***(1): 2. DOI: 10.1007/s40866-025-00316-7.

[2] H. J. Kim and M. K. Kim, (2025) *"Data-Driven Virtual Power Plant Bidding Strategy in Electricity Markets Integrating Hybrid Forecasting Model and Customized Incentive Demand Response"* **IEEE Internet of Things Journal *12***(10): 13851–13869. DOI: 10.1109/JIOT.2024.3525060.

[3] F. A. Nahid et al., (2024) *"Short-Term Customer-Centric Electric Load Forecasting for Low Carbon Microgrids Using a Hybrid Model"* **Energy Systems**: 1–57. DOI: 10.1007/s12667-024-00704-5.

[4] V. Arabzadeh and R. Frank, (2025) *"A Four-Dimensional Analysis of Explainable AI in Energy Forecasting: A Domain-Specific Systematic Review"* **Machine Learning and Knowledge Extraction *7***(4): 153. DOI: 10.3390/make7040153.

[5] M. A. El-Shorbagy et al., (2024) *"Bald Eagle Search Algorithm: A Comprehensive Review with Its Variants and Applications"* **Systems Science & Control Engineering *12***(1): 2385310. DOI: 10.1080/21642583.2024.2385310.

[6] X. Mao et al., (2025) *"Simplicity in Dynamic and Competitive Electricity Markets: A Case Study on Enhanced Linear Models versus Complex Deep-Learning Models for Day-Ahead Electricity Price Forecasting"* **Applied Energy *383***: 125201. DOI: 10.1016/j.apenergy.2024.125201.

[7] Q. Tang et al., (2024) *"Forecasting Individual Bids in Real Electricity Markets through Machine Learning Framework"* **Applied Energy *363***: 123053. DOI: 10.1016/j.apenergy.2024.123053.

[8] F. Li et al., (2024) *"Optimization of Electricity Retail Packages under the Spot Market Mode Accounting for Customer Response"* **IEEE Access *12***: 90112–90123. DOI: 10.1109/ACCESS.2024.3410991.

[9] A. Mohsenimanesh, C. McNevin, and E. Entchev, (2025) *"EV and Renewable Energy Integration in Residential Buildings: A Global Perspective on Deep Learning, Strategies, and Challenges"* **World Electric Vehicle Journal *16***(11): 603. DOI: 10.3390/wevj16110603.

[10] S. Makaremi, (2025) *"A Multi-Output Deep Learning Model for Energy Demand and Port Availability Forecasting in EV Charging Infrastructure"* **Energy *317***: 134582. DOI: 10.1016/j.energy.2025.134582.

[11] M. R. Mansor, M. K. Ajiriyanto, R. Kriswarini, B. Soegijono, S. D. Yudanto, D. Nanto, C. Rosyidan, and F. B. Susetyo, (2025) *"Ni Layer Fabrication in Various Temperature of Watts Solution"* ***28***(4): 853–864. DOI: 10.6180/jase.202504_28(4).0016.

[12] S. Alshahr et al., (2026) *"Dynamic Renewable Energy Integration for EV Charging via Model-Based Reinforcement Learning"* **Ain Shams Engineering Journal *17***(3): 104040. DOI: 10.1016/j.asej.2026.104040.

[13] M. Waqar, Y.-W. Kim, and Y.-C. Byun, (2026) *"A Hybrid Deep Learning Framework for Multivariate Energy Forecasting and Peak Load Prediction in Electric Vehicle Charging Infrastructure"* **Applied Energy *402***: 126964. DOI: 10.1016/j.apenergy.2025.126964.

[14] F. Aksan, V. Suresh, and P. Janik, (2024) *"Optimal Capacity and Charging Scheduling of Battery Storage through Forecasting of Photovoltaic Power Production and Electric Vehicle Charging Demand with Deep Learning Models"* **Energies *17***(11): 2718. DOI: 10.3390/en17112718.

[15] N. Tsalikidis et al. "Hybrid CNN-LSTM Forecasting Model for Electric Vehicle Charging Demand in Smart Buildings". In: *Proceedings of the 6th Global Power, Energy and Communication Conference (GPECOM)*. 2024, 590–595. DOI: 10.1109/GPECOM61896.2024.10582629.