iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80607

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

A Review of Artificial Intelligence Techniques for Power Market Spot Price Forecasting

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Abstract: Electricity spot price forecasting has become a critical component in modern deregulated power markets due to significant price volatility, uncertainty, and the growing integration of renewable energy sources. Accurate prediction of these prices is essential for effective decision-making by market participants, including generators, system operators, and consumers. In recent years, Artificial Intelligence (AI) techniques have gained prominence for their ability to capture complex and nonlinear relationships inherent in electricity market dynamics. This paper presents a comprehensive review of AI-based approaches for electricity spot price prediction, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy Logic systems, and advanced deep learning models such as Long Short-Term Memory (LSTM) networks. Furthermore, the study provides a comparative analysis of traditional statistical methods and modern AI techniques, highlighting their advantages and limitations. Key challenges such as data uncertainty, market volatility, and renewable energy variability are discussed, along with existing research gaps. Finally, potential future research directions are outlined, focusing on hybrid models, real-time forecasting, and intelligent energy market frameworks.
Keywords: Electricity Market, Spot Price Prediction, Artificial Intelligence, ANN, LSTM, Forecasting

I. INTRODUCTION

The electric power sector has undergone a significant transformation over the past few decades, shifting from traditionally regulated monopolies to competitive and deregulated market structures. In such modern electricity markets, generation, transmission, and distribution are often operated by separate entities, and electricity is traded as a commodity. This restructuring has introduced market-based pricing mechanisms where electricity prices are determined dynamically based on supply–demand balance, transmission constraints, and operational conditions of the power system. As a result, electricity prices exhibit high volatility and uncertainty compared to conventional energy markets. Accurate prediction of electricity spot prices has therefore become essential for various stakeholders, including power producers, consumers, traders, and system operators. Reliable forecasts enable generators to develop optimal bidding strategies, assist consumers in minimizing energy costs, and support system operators in maintaining grid stability and efficient market operation. Furthermore, price forecasting plays a critical role in risk management, contract negotiation, and investment planning in the energy sector. However, electricity price behavior is highly nonlinear, influenced by multiple factors such as load demand, renewable energy generation, fuel prices, weather conditions, and transmission congestion. Traditional statistical and time-series models often struggle to capture these complex relationships effectively. To address these challenges, Artificial Intelligence (AI) techniques have emerged as powerful tools for electricity price forecasting. Methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Fuzzy Logic systems, and advanced deep learning models like Long Short-Term Memory (LSTM) networks have demonstrated superior performance in modeling nonlinear and dynamic patterns in electricity markets. The objective of this review paper is to provide a comprehensive analysis of AI-based approaches for electricity spot price prediction. This study examines various traditional and modern forecasting techniques, compares their strengths and limitations, and highlights key challenges faced in practical applications. Additionally, the paper identifies existing research gaps and discusses future directions, including the integration of advanced AI models, real-time forecasting frameworks, and intelligent energy market systems.

II. MOTIVATION AND OBJECTIVE OF RESEARCH

The restructuring of electricity markets has led to dynamic and competitive pricing environments where electricity spot prices are highly volatile and uncertain due to factors such as load demand variations, renewable energy integration, transmission constraints, and changing operational conditions.

Accurate prediction of these prices is essential for efficient market operation, optimal bidding strategies, and effective risk management. However, traditional forecasting methods and basic machine learning models are often unable to capture the complex nonlinear relationships and network dependencies present in power systems, resulting in limited prediction accuracy, especially during congestion and price spike conditions. In addition, the continuously evolving nature of electricity markets, influenced by factors such as fuel price changes, policy regulations, and renewable energy variability, requires forecasting models to be adaptive and robust. Therefore, the objective of this research is to develop an advanced Artificial Intelligence-based framework for electricity spot price prediction that integrates power system operational characteristics, network topology, and data-driven learning techniques. The proposed approach aims to generate realistic datasets using Optimal Power Flow methods, apply advanced machine learning and deep learning models for accurate price forecasting, incorporate system constraints to improve prediction reliability, and develop an adaptive system capable of handling changing market conditions. Ultimately, the research seeks to provide a reliable and efficient forecasting tool that can support market participants, system operators, and energy traders in making informed decisions and improving overall market performance.

III. LITERATURE REVIEW

Electricity price forecasting has become an important area of research due to its critical role in the efficient operation of deregulated power markets. Over time, forecasting techniques have evolved from traditional statistical models to advanced Artificial Intelligence (AI) and deep learning approaches.

Initially, models such as ARIMA and GARCH were used for electricity price prediction, as they could capture linear trends and price volatility. However, these methods were limited in handling the nonlinear and highly dynamic nature of electricity markets, especially during demand fluctuations and congestion conditions. With advancements in computational methods, machine learning techniques have been widely adopted, offering improved accuracy by learning complex patterns from historical data. In addition, hybrid models, such as GRU combined with LightGBM and Bi-LSTM with CatBoost, have been developed to enhance forecasting performance by capturing both temporal and nonlinear relationships.

More recently, deep learning models like LSTM and CNN-LSTM have shown superior performance in modeling time-series data and capturing both temporal and spatial dependencies. Furthermore, ANN-based approaches integrated with power system models, such as Optimal Power Flow (OPF), have improved prediction realism by incorporating system constraints.

Despite these advancements, existing methods still face challenges, including limited consideration of network topology and transmission constraints, as well as poor adaptability to changing market conditions. These limitations highlight the need for more advanced and integrated forecasting frameworks.

Table1. Comparative Analysis of Existing Methods for Electricity Price Prediction

Sr. No.	Author & Year	Method Used	Key Contribution
1.	Chen et al. (2025)	Machine Learning	Developed a model for regional electricity price prediction with improved accuracy for short- and medium-term forecasting.
Sr. No.	Author & Year	Method Used	Key Contribution
2.	Han et al. (2024)	Machine Learning	Proposed data-driven approaches to enhance forecasting performance in competitive markets.
3.	Li et al. (2024)	GRU + LightGBM	Introduced a hybrid model combining temporal learning and boosting for accurate day-ahead prediction.
4.	Lu et al. (2024)	Probability Forecasting	Developed a probabilistic method for early detection of electricity price volatility.
5.	Zhang et al. (2022)	Bi-LSTM + CatBoost	Proposed a hybrid deep learning model for improved short-term electricity price prediction.

6.	Miletic et al. (2022)	LSTM	Applied LSTM networks for effective day-ahead electricity price forecasting.
7.	Zhou and Gao (2022)	CNN-LSTM	Developed an attention-based model capturing spatial and temporal dependencies.
8.	Zeng et al. (2021)	Deep Learning	Compared deep learning models and demonstrated improved performance over traditional methods.
9.	Zhang and Fleyeh (2019)	ANN	Analyzed the effectiveness of ANN models for electricity spot price prediction.
10.	Warkad et al. (2012)	ANN + OPF	Proposed ANN-based nodal price prediction incorporating power system constraints.

IV. ELECTRICITY PRICE FORECASTING

Electricity price forecasting is a fundamental aspect of modern power market operations, as it supports efficient decision-making for market participants, including generators, consumers, and system operators. Accurate forecasting helps in optimizing bidding strategies, improving system reliability, and reducing financial risks. Electricity price forecasting can be broadly classified based on the forecasting horizon and the pricing mechanism used in the market.

Based on the forecasting horizon, electricity price prediction is categorized into short-term, medium-term, and long-term forecasting. Short-term forecasting typically covers a time period ranging from a few minutes to one day ahead. It is mainly used for real-time market operations, load dispatch, and day-ahead trading. Medium-term forecasting spans from a few weeks to several months and is useful for maintenance scheduling, contract planning, and resource allocation. Long-term forecasting extends from several months to years and is primarily applied for investment planning, policy formulation, and infrastructure development in the power sector.

In addition to time-based classification, electricity prices can also be categorized based on the pricing mechanism. One of the most widely used pricing approaches is the nodal price, also known as Locational Marginal Price (LMP). Nodal pricing represents the cost of supplying electricity at a specific location in the network while considering factors such as generation cost, transmission losses, and network congestion. It provides a more accurate and location-specific representation of electricity prices across the power system.

Another commonly used pricing mechanism is the market clearing price (MCP), which is determined by the intersection of supply and demand curves in the electricity market. MCP represents a uniform price at which electricity is traded within a market for a given time interval. Although it is simpler compared to nodal pricing, it does not explicitly account for transmission constraints and network conditions.

V. TRADITIONAL METHODS

Traditional approaches for electricity price forecasting are primarily based on statistical and time-series models such as Auto-Regressive Integrated Moving Average (ARIMA), Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH), and other classical time-series techniques. ARIMA models are widely used for analyzing historical price data and capturing linear trends, seasonality, and temporal patterns. Similarly, GARCH models are effective in modeling the volatility and variance of electricity prices over time, making them useful for understanding price fluctuations in the market.

In addition to these methods, various time-series models have been applied to forecast electricity prices based on past observations and statistical relationships. These models are relatively simple to implement and require less computational effort compared to advanced techniques.

However, despite their advantages, traditional methods have significant limitations. Electricity price behavior is highly nonlinear and influenced by multiple dynamic factors such as load demand variations, renewable energy integration, and transmission constraints. Traditional statistical models are not capable of effectively capturing these nonlinear relationships, which results in reduced prediction accuracy, particularly during sudden market changes and extreme price conditions.

VI. AI-BASED METHODS

Artificial Intelligence (AI) techniques have become highly effective tools for electricity price forecasting due to their ability to model complex, nonlinear, and dynamic relationships in power markets. Unlike traditional methods, AI-based models can learn patterns directly from data without requiring explicit mathematical formulations. This section presents the major AI techniques used in electricity price prediction.

A. Artificial Neural Network (ANN)

Artificial Neural Networks are among the most widely used AI techniques for electricity price forecasting. These models are inspired by the structure of the human brain and consist of interconnected neurons that process input data and generate output predictions. ANN models are capable of capturing nonlinear relationships between multiple input variables such as load demand, generation levels, and market conditions. Due to their flexibility and strong learning capability, ANN-based models have been successfully applied in short-term electricity price prediction.

B. Support Vector Machine (SVM)

Support Vector Machines are powerful supervised learning models used for regression and classification tasks. In electricity price forecasting, SVM models are known for their high accuracy and strong generalization capability, especially when dealing with small or limited datasets. These models work by finding an optimal boundary that minimizes prediction error, making them robust against overfitting and noise in the data.

C. Fuzzy Logic

Fuzzy Logic-based models are designed to handle uncertainty and imprecision in data, which is a common characteristic of electricity markets. These models use linguistic rules and membership functions to represent complex relationships in a more interpretable manner. Fuzzy systems are easy to understand and can incorporate expert knowledge, making them suitable for applications where data uncertainty is significant.

D. Hybrid Models

Hybrid models combine two or more techniques to improve forecasting performance. For example, Artificial Neural Networks combined with wavelet transform can effectively capture both time-frequency characteristics and nonlinear patterns in electricity price data. Similarly, models such as Self-Organizing Maps (SOM) combined with Support Vector Machines enhance clustering and prediction accuracy. These hybrid approaches leverage the strengths of individual models to achieve better performance and robustness.

E. Deep Learning Models

Deep learning techniques have gained significant attention in recent years due to their superior performance in handling large and complex datasets. Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNN) are particularly effective for time-series forecasting, as they can capture long-term dependencies in electricity price data. Additionally, Graph Neural Networks (GNN) are emerging as powerful tools for modeling the network structure of power systems, enabling more accurate prediction of nodal electricity prices by considering spatial relationships and system topology.

VII. PROPOSED METHODOLOGY

This research proposes a multi-stage Artificial Intelligence-based framework for electricity spot price prediction that integrates power system modeling, graph-based learning, optimization consistency, uncertainty estimation, and adaptive learning. The overall methodology is designed to overcome the limitations of existing forecasting approaches by incorporating both physical system characteristics and data-driven intelligence. The proposed framework consists of five major components: ACDC-OPF Digital Twin Scenario Distiller (ADOSD), Constraint-Encoded Graph Price Network (CE-GPN), KKT-Residual Price Calibrator (KRPC), Conformal Risk Envelope Forecaster (CREF), and Regime-Drift Continual Market Learner (RDCML).

A. AC/ DC OPF Digital Twin Scenario Distiller (ADOSD)

This framework integrates AC/DC OPF, digital twin dynamics, and AI-based scenario distillation for efficient electricity pricing.

1. AC/DC OPF Optimization

$$\min_{x,u} \sum_{i \in G} C_i \left(P_i^g\right) + \sum_{k \in DC} C_k \left(P_k^{dc}\right)$$

Subject to:

AC Power Flow

$$P_i^g - P_i^d = V_i \sum_j V_j \left(G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}\right)$$

$$Q_i^g - Q_i^d = V_i \sum_j V_j \left(G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}\right)$$

DC Power Flow

$$P_{ij}^{dc} = \frac{V_{dc,i} - V_{dc,j}}{R_{ij}^{dc}}, P_i^{conv} = \eta_i P_{ij}^{dc}$$

Constraints

$$P_i^{min} \le P_i^g \le P_i^{max}, V_i^{min} \le V_i \le V_i^{max}$$

$$| S_{ij} | \le S_{ij}^{max}, P_k^{dc,min} \le P_k^{dc} \le P_k^{dc,max}$$

2. Digital Twin Model

$$x_{t+1} = f(x_t, u_t, w_t), y_t = h(x_t)$$

3. Scenario Distillation

$$D^* = \arg \min_{S \subset D} \mathcal{L}(f_\theta, S), | S | \ll | D |$$

4. Loss Function

$$\mathcal{L} = \alpha \parallel \hat{y} - y \parallel^2 + \beta \parallel g(x,u) \parallel^2 + \gamma \parallel \hat{\lambda} - \lambda \parallel^2$$

5. Price (LMP)

$$\lambda_i = \frac{\partial \mathcal{L}}{\partial P_i^d} = \lambda^{energy} + \lambda^{loss} + \lambda^{congestion}$$

6. AI Surrogate Model

$$\hat{z} = f_\theta(x)$$

7. Final Optimization

$$\min_{\theta, D^*} \mathcal{L}(f_\theta, D^*) \text{s.t. OPF} + \text{Digital Twin}$$

B. Constraint-Encoded Graph Price Network (CE-GPN)

The second stage employs a graph-based deep learning model to predict electricity prices across the network. Since power systems inherently have a graph structure, with buses as nodes and transmission lines as edges, a Graph Neural Network (GNN) is used to capture spatial dependencies and network topology.

The CE-GPN models the power system as a graph and predicts nodal electricity prices using a constraint-aware Graph Neural Network (GNN).

1. Graph Representation

$\mathcal{G} = (\mathcal{V}, \mathcal{E})$

$\mathcal{V}$: set of buses (nodes)

- $\mathcal{E}$: set of transmission lines (edges)

Node features:

$x_i = [P_i^d, P_i^g, V_i, \theta_i]$

2. Graph Neural Network Propagation

$$h_i^{(k+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} W^{(k)} h_j^{(k)} + B^{(k)} h_i^{(k)}\right)$$

Where:

- $h_i^{(k)}$: node embedding
- $\mathcal{N}(i)$: neighboring buses
- $W^{(k)}, B^{(k)}$: learnable weights

3. Price Prediction

$$\hat{\lambda}_i = f_\theta(h_i^{(K)})$$

Where:

- $\hat{\lambda}_i$: predicted nodal price (LMP)

4. Constraint Encoding (Physics-Aware Loss)

$$\mathcal{L} = \underbrace{\| \hat{\lambda} - \lambda \|^2}_{\text{prediction}} + \beta \underbrace{\| g(x) \|^2}_{\text{power flow constraints}}$$

5. Final Objective

$$\min_\theta \mathcal{L}$$

C. KKT-Residual Price Calibrator (KRPC)

The KRPC refines predicted prices from CE-GPN by enforcing Karush-Kuhn-Tucker (KKT) optimality conditions of the OPF problem to ensure physical and economic consistency.

1. OPF Lagrangian

$$\mathcal{L}(x, \lambda, \mu) = C(P^g) + \lambda^T g(x) + \mu^T h(x)$$

Where:

- $g(x)$: equality constraints (power balance)
- $h(x)$: inequality constraints (limits)
- λ, μ: Lagrange multipliers

2. KKT Conditions

Stationarity

$$\nabla_x \mathcal{L} = 0$$

Primal feasibility

$$g(x) = 0, h(x) \leq 0$$

Dual feasibility

$$\mu \geq 0$$

Complementary slackness

$$\mu \cdot h(x) = 0$$

3. KKT Residual

$$r_{KKT} = \| \nabla_x \mathcal{L} \| + \| g(x) \| + \| \min(0, h(x)) \|$$

4. Price Calibration

$\lambda_i^{cal} = \hat{\lambda}_i - \alpha \cdot r_{KKT}$

Where:

- $\hat{\lambda}_i$: CE-GPN predicted price
- λ_i^{cal}: calibrated price

5. Loss Function

$\mathcal{L} = \| \lambda^{cal} - \lambda^{true} \|^2 + \beta \cdot r_{KKT}$ Although the CE-GPN model provides accurate.

D. Conformal Risk Envelope Forecaster (CREF)

Electricity prices are highly uncertain, and single-point predictions may not be sufficient for practical decision-making. Therefore, the fourth stage introduces an uncertainty estimation mechanism using conformal prediction techniques. The CREF provides uncertainty-aware electricity price forecasting using conformal prediction, generating prediction intervals with guaranteed confidence.

1. Point Prediction

$\hat{\lambda}_i = f_\theta(x_i)$

2. Nonconformity Score (Calibration Set)

$\alpha_i = | \lambda_i - \hat{\lambda}_i |$

3. Quantile Threshold

$q_{1-\epsilon} = \text{Quantile}_{1-\epsilon}(\{\alpha_i\})$

Where:

- ϵ: error level (e.g., 0.05 for 95% confidence)

4. Prediction Interval (Risk Envelope)

$\lambda_i \in [\hat{\lambda}_i - q_{1-\epsilon}, \hat{\lambda}_i + q_{1-\epsilon}]$

5. Adaptive Risk Adjustment

$q_{1-\epsilon}^t = q_{1-\epsilon} \cdot (1 + \gamma \sigma_t)$

Where:

- σ_t: system volatility (load/renewable uncertainty)

6. Coverage Guarantee

$P(\lambda_i \in \text{Interval}) \geq 1 - \epsilon$

E. Regime-Drift Continual Market Learner (RDCML)

Electricity markets are dynamic and continuously evolving due to factors such as policy changes, fuel price variations, and renewable energy integration. To address this challenge, the final stage introduces a continual learning mechanism.

The RDCML enables adaptive electricity price forecasting by detecting regime shifts and updating the model through continual learning.

1. Online Prediction Model

$\hat{\lambda}_t = f_{\theta_t}(x_t)$

2. Regime Drift Detection

Statistical drift measure:

$D_t = \| P_t(x) - P_{t-1}(x) \|$

Drift condition:

$D_t > \delta \quad \Rightarrow \quad \text{Regime Change}$

Where:

- $P_t(x)$: data distribution at time t
- δ: drift threshold

3. Incremental Learning Update

$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}(f_{\theta_t}, \mathcal{D}_t)$

4. Knowledge Retention (Regularization)

$\mathcal{L}_{total} = \mathcal{L}_{new} + \lambda \parallel \theta_t - \theta_{old} \parallel^2$

5. Memory Replay (Optional)

$\mathcal{D}_{train} = \mathcal{D}_t \cup \mathcal{D}_{memory}$

6. Adaptive Forecasting

$f_{\theta_t} \rightarrow f_{\theta_{t+1}}$ (updated under drift)

VIII. CHALLENGES

Electricity price forecasting is a complex task due to several inherent challenges in power market operations. One of the major challenges is the high volatility of electricity prices, which fluctuate rapidly due to changes in demand, supply, and system conditions. The increasing integration of renewable energy sources such as wind and solar introduces additional uncertainty, as their generation is intermittent and difficult to predict accurately. Another significant challenge is the limitation of available data, including issues such as incomplete datasets, noise, and lack of real-time information, which can negatively affect model performance. Furthermore, transmission congestion and network constraints play a crucial role in price formation, making it difficult for forecasting models to accurately capture spatial variations in electricity prices across the power system.

IX. RESEARCH GAP

Despite the significant progress in electricity price forecasting techniques, several research gaps still exist. Many existing approaches do not fully utilize advanced Artificial Intelligence models capable of capturing complex system behavior and network dependencies. There is also limited focus on real-time price prediction, which is essential for modern power system operations and dynamic market environments. Additionally, current models often lack effective mechanisms for handling uncertainty, particularly during extreme market conditions such as price spikes and sudden demand changes. These gaps highlight the need for more advanced, adaptive, and integrated forecasting frameworks.

X. CONCLUSION & FUTURE SCOPE

Electricity price forecasting is essential for efficient operation of deregulated power markets. While traditional statistical methods struggle with nonlinear and dynamic price behavior, AI-based approaches—such as machine learning, deep learning, and hybrid models—offer higher accuracy and better adaptability to complex market patterns. However, challenges like high price volatility, renewable energy uncertainty, and limited data quality continue to impact performance. Hence, more robust and adaptive forecasting frameworks are required for reliable decision-making.

Future research should focus on scalable deep learning models capable of handling large, complex datasets and real-time inputs. Integration with smart grid infrastructure will enhance data availability and system awareness. Additionally, combining AI with optimization and power system models can improve forecasting accuracy, reliability, and practical deployment in dynamic electricity markets.

REFERENCES

[1] Zhongyang Chen, Xiaogang Li, Min Wu, Mengge Zhang (2025), "Research on Regional Electricity Price Forecasting Based on Machine Learning Algorithms," 2025 IEEE 12th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)

[2] Lijia Han, Chan Ban, Cong Zhang, Lize Liu (2024), "Electricity Price Forecasting in Power Markets Based on Machine Learning," 2024 IEEE 4th International Conference on Digital Twins and Parallel Intelligence (DTPI)

[3] Junlong Li, Chao Zhang, Peipei You, Shuo Yin, Yao Lu, Chengren Li (2024), "A Hybrid GRU LightGBM Model for Day-Ahead Electricity Price Forecasting," 2024 3rd International Conference on Energy and Electrical Power Systems (ICEEPS), IEEE

[4] Yao Lu, Junhui Liu, Shuo Yin (2024), "Research on Probability Density Forecasting Method of Coordinated Load for Short-and Medium-Term Price Early-Warning of Spot Electricity Market," 2024 IEEE 3rd International Conference on Energy and Electrical Power Systems (ICEEPS)

[5] Zhang, F.; Fleyeh, H.; Bales, C. (2022), "A hybrid model based on bidirectional long short term memory neural network and CatBoost for short-term electricity spot price forecasting," Journal of the Operational Research Society, 73, 301–325

[6] Miletic, M.; Pavic, I.; Pandzic, H.; Capuder, T. (2022), "Day-ahead Electricity Price Forecasting Using LSTM Networks," 2022 7th International Conference on Smart and Sustainable Technologies (SpliTech)

[7] B. Zhou and W. Gao (2022), "Improving day ahead electricity price forecasting accuracy using attention-based CNN-LSTM," IEEE Access, vol. 10, pp. 9732–9742
[8] Z. Zeng, D. Wang, X. Liu (2021), "Day-ahead electricity price forecasting using deep learning models," IEEE Access, vol. 9, pp. 32710–32720
[9] Zhang & Fleyeh (2019), "A Review of Single Artificial Neural Network Models for Electricity Spot Price Forecasting," Journal Paper
[10] S. B. Warkad, Dr. M.K. Khedkar, Dr. G. M. Dhole, "Day-Ahead AC-DC OPF Based Nodal Price Prediction by Artificial Neural Networks (ANNs) in a Restructured Electricity Market", International Journal of Power and Energy Conversion (IJPEC), (ISSN: 1757-1154), InderScience Publications (Scopus Elsevier), Volume 3, Issue 1/2, pp.54-76, 2012. DOI: 10.1504/IJPEC.2012.044284"
[11] O'Connor, C., Collins, J., Prestwich, S., et al (2024). Electricity Price Forecasting in the Irish Balancing Market. Energy Strategy Reviews. https://doi.org/10.1016/j.esr.2024.101436
[12] Huang, Y., Zhu, Y., Lei, G., et al (2025). LLM-Enhanced Short-Term Electricity Price Forecasting Method for Australian Electricity Market. Applied Sciences. https://doi.org/10.3390/app16010200
[13] Osone, Y., Kodaira, D. (2025). Quantile Regression for Probabilistic Electricity Price Forecasting in the U.K. Electricity Market. IEEE Access. https://doi.org/10.1109/access.2025.3528450
[14] Heistrene, L., Machlev, R., Perl, M., et al (2023). Explainability-based Trust Algorithm for electricity price forecasting models. Energy and AI. https://doi.org/10.1016/j.egyai.2023.100259
[15] Tehrani, S., Juan, J., Caro, E. (2022). Electricity Spot Price Modeling and Forecasting in European Markets. Energies. https://doi.org/10.3390/en15165980
[16] Popovska, E., Georgieva-Tsaneva, G. (2022). ARIMA Model for Day-Ahead Electricity Market Price Forecasting. Innovative STEM Education. https://doi.org/10.55630/stem.2022.0418
[17] Hanif, M., Shahzad, M., Mehmood, V., et al (2023). EPFG: Electricity Price Forecasting with Enhanced GANS Neural Network. IETE Journal of Research. https://doi.org/10.1080/03772063.2021.2000510
[18] Mehrdoust, F., Noorani, I., Belhaouari, S. (2023). Forecasting Nordic electricity spot price using deep learning networks. Neural Computing and Applications. https://doi.org/10.1007/s00521-023-08734-3