

# Advancing Electricity Price Forecasting: A Comprehensive Framework Integrating Ensemble Learning, Deep Learning, and Large Language Models

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**Abstract:** Electricity price forecasting (EPF) is essential for daily energy market operations, helping participants optimize bidding strategies and make informed decisions by predicting price fluctuations accurately. Electricity price forecasting (EPF) plays a pivotal role in the operational dynamics of energy markets, facilitating optimized bidding strategies and informed decision-making for market participants through accurate prediction of price fluctuations. This study proposes a comprehensive methodological framework for EPF, integrating four principal approaches: ensemble learning, deep learning, large language models (LLMs), and the fusion of LLMs with retrieval-augmented generation (RAG). Ensemble learning leverages the complementary strengths of base models such as ARIMA, Support Vector Regression (SVR), and Random Forest Regression, while deep learning architectures, including LSTM, GRU, and Transformer, are employed to model complex temporal dependencies and long-term patterns inherent in electricity price data. Large language models, fine-tuned with domain-specific datasets, enhance predictive accuracy by harnessing advanced natural language processing capabilities. The RAG-enhanced LLM approach further refines forecasting precision by incorporating external knowledge retrieved from a structured knowledge graph. Collectively, these methodologies form a robust and versatile framework designed to address the inherent complexities and uncertainties of electricity markets, thereby supporting efficient power dispatch and market operations. This research underscores the evolving landscape of EPF methodologies and their potential to enhance grid reliability, operational efficiency, and the integration of

renewable energy sources, ultimately contributing to the development of a more resilient and sustainable energy ecosystem.

**Keywords:** Electricity Price Forecasting (EPF); Large Language Models (LLMs); Renewable Energy Integration; Ensemble Learning

## 1. Introduction

As the cornerstone of the modern economy, the stable operation of the electricity market has a profound impact on people's livelihoods, commerce, and national security. However, the complexity and uncertainty of the electricity market make its prediction fraught with challenges [1]. Factors such as weather changes, demand fluctuations, and fuel costs collectively influence the supply and demand of electricity, making it difficult to accurately forecast market prices and supply stability. For instance, extreme weather can trigger surges in electricity demand or fluctuations in renewable energy output, climate conditions significantly impact power generation and electricity demand, with these effects expected to grow, especially during winter heating peaks and summer cooling periods [2]. Changes in fuel prices directly affect power generation costs. The deployment and performance of these energy sources (operational management of renewable energy sources, such as solar, wind, and hydropower) are inherently contingent upon natural variables, including meteorological conditions and temperature variations [2]. Additionally, the growth in electricity demand is closely tied to economic development and industrial restructuring, further complicating market predictions. A critical aspect of electricity demand forecasting is the recognition that, while numerous variables may correlate with electricity consumption, incorporating all of them into a real-time monitoring and

surveillance system is neither feasible nor practical [3]. This limitation necessitates the identification and prioritization of the most influential factors to ensure efficient and accurate demand prediction within operational constraints. Therefore, in-depth research into the dynamic mechanisms of the electricity market and the development of accurate forecasting models are of great significance for ensuring the stability of the power system, optimizing resource allocation, and promoting sustainable economic development. Accurate and stable load forecasting is essential for the daily operation of power systems and serves as a cornerstone for constructing a modernized power infrastructure.[4] Precise power load forecasting is indispensable for all power supply sectors, as it provides critical decision-making support to address imbalances between power supply and demand. By enabling proactive adjustments and optimized resource allocation, it enhances grid reliability, operational efficiency, and the integration of renewable energy sources, ultimately contributing to a more resilient and sustainable energy system.

## 2. Related Work

In the field of electricity price prediction and electricity market analysis, a lot of research has focused on the application of statistical methods, machine learning algorithms and deep learning models. First, traditional statistical methods such as time series analysis (such as ARIMA, SARIMA) and regression analysis are widely used in electricity price prediction, which provide a basic forecasting framework by capturing the trend and seasonal characteristics of historical electricity price data. Secondly, with the development of machine learning technology, algorithms such as support vector machine (SVM), Random Forest and gradient Lift Tree (GBDT) have been introduced into the power market, which can handle nonlinear relations and high-dimensional data, significantly improving the prediction accuracy. In recent years, deep learning models, especially recurrent neural networks (RNNS) and their variants Long Short-Term memory networks (LSTMS) and gated cycle units (GRUs), have excelled in electricity price prediction, which can effectively capture long-term dependencies in time series data and is suitable for complex dynamic changes in the

electricity market. Ultra-short-term power load forecasting involves utilizing historical load data and weather information from the preceding few hours to predict the load for the upcoming hour [4]. This forecasting approach plays a critical role in optimizing power dispatch operations and supporting the establishment of efficient power spot markets. By providing timely and accurate load predictions, it enables grid operators to balance supply and demand effectively, ensuring system stability and reducing operational costs. Taken together, statistical methods provide the basis for electricity price prediction, machine learning algorithms further optimize prediction performance, and deep learning models such as RNN, LSTM, and GRU show strong potential in processing high-dimensional, non-linear time series data of power markets. Electricity price forecasting (EPF) has attracted considerable attention for more than two decades, driven by the global trend of electricity market deregulation[5]. Over the years, a wide range of models and methodologies have been developed and applied in the literature on EPF. These approaches can be broadly classified into five primary categories: game theory models, fundamental models, reduced-form models, statistical models, and machine learning models. Each category offers unique insights and tools for addressing the complexities and uncertainties inherent in electricity price prediction, reflecting the evolving nature of research in this field.

## 3. Method

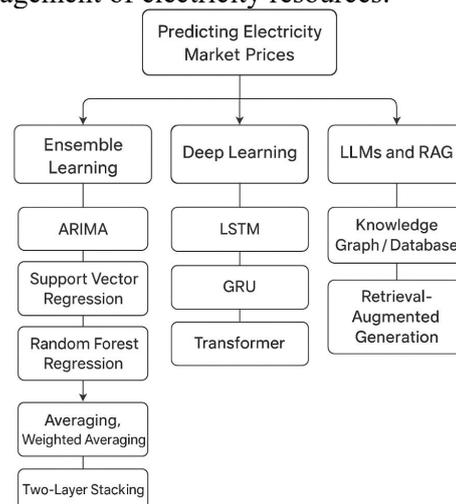
The methodology for predicting electricity market prices integrates four advanced approaches, which is shown in the Fig.1 : ensemble learning, deep learning, large language models (LLMs), and the combination of LLMs with retrieval-augmented generation (RAG). Each approach contributes unique strengths and capabilities, creating a comprehensive framework for accurately forecasting electricity prices.

Ensemble learning leverages multiple base models to enhance the robustness and accuracy of predictions by combining their complementary strengths. In this approach, three key models are utilized: ARIMA (AutoRegressive Integrated Moving Average), Support Vector Regression (SVR), and Random Forest Regression. ARIMA is effective for

modeling linear time series data, capturing temporal dependencies by considering previous values and their differences. This model is particularly useful for identifying trends and seasonality in electricity price data. SVR is designed to model nonlinear relationships, finding a hyperplane that best fits the data while minimizing errors. It is highly effective for capturing complex, nonlinear patterns in electricity prices. Random Forest Regression, an ensemble of decision trees, handles high-dimensional data and complex interactions between features, providing reliable predictions by averaging over multiple trees. Simple strategies like averaging or weighted averaging combine the predictions of individual models to produce a final result. Additionally, a two-layer stacking approach is employed, where the outputs of the base models are used as inputs for a second-layer model, typically linear regression, which further refines the predictions and improves accuracy by considering interactions between the base models.

In the deep learning approach, advanced neural network architectures are utilized to model intricate temporal dependencies and long-term patterns in electricity price data. LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) networks are particularly effective for handling sequential data. These models maintain memory of past time steps, which allows them to capture long-term dependencies that are crucial when predicting electricity prices based on historical data. The Transformer model, known for its self-attention mechanism, excels in capturing long-range dependencies across time steps. It employs multi-head attention to focus on different parts of the input sequence simultaneously, and feedforward neural networks to learn complex patterns in the data. Optimization algorithms such as Adam are employed to adjust model parameters and minimize loss functions like mean squared error (MSE), ensuring that the models make accurate predictions. The combination of large language models (LLMs) with retrieval-augmented generation (RAG) introduces external knowledge to improve prediction accuracy. A knowledge graph or database is constructed, containing essential information such as electricity market data, economic indicators, and meteorological data. This external knowledge serves as a rich source of contextual information, which is incorporated into the prediction process. When making a prediction, the RAG framework retrieves relevant information from the knowledge graph based on the input time series

data and specific queries. This information is then fused with the input data before being fed into the LLM. The LLM generates predictions based on the enriched input, which is now informed by both historical data and additional contextual factors like weather patterns and economic trends. Continuous optimization is applied to both the retrieval strategy and the model parameters, ensuring that the LLM consistently improves its predictions over time. The integration of these four approaches—ensemble learning, deep learning, LLMs, and RAG—forms a powerful and multi-layered framework for electricity price forecasting. Ensemble learning ensures that individual model strengths are leveraged, deep learning captures complex temporal patterns, and LLMs combined with RAG enrich the predictions by incorporating external knowledge. This comprehensive methodology addresses the inherent complexities and uncertainties of the electricity market, supporting improved decision-making in power dispatch and market operations. The combination of these techniques provides a more accurate, reliable, and contextually aware approach to forecasting electricity prices, which is critical for both market participants and grid operators. By enhancing the precision of pricing predictions, this methodology contributes to improving market efficiency and enabling better management of electricity resources.



**Figure 1. The Framework of Our Work**

**4. Experiment**

The experimental evaluation of the proposed hybrid model for forecasting electricity market prices was conducted using day-ahead market clearing price data obtained from the CAISO

(California Independent System Operator) for the period 2019-2024, with an hourly resolution. This dataset also included critical covariates such as load demand, temperature, and fuel prices. The preprocessing pipeline applied time-series-specific techniques, including linear interpolation for short-term missing data and moving average imputation for longer gaps. Seasonal components were decomposed using the STL method (Seasonal and Trend decomposition using Loess), while feature engineering involved generating lagged features (24-hour lag), rolling statistics (7-day moving averages), and volatility indicators (standard deviation over a 30-day window). The data was split chronologically into training (2019-2022), validation (2023), and test sets (2024).

For comparative evaluation, three baseline models were implemented to benchmark performance: (1) A seasonal ARIMA model, optimized using the ADF test and ACF/PACF analysis for parameter selection. (2) An XGBoost implementation, with tree depth set to 6 and learning rate at 0.1. (3) A single-layer LSTM network, with 128 hidden units and a dropout rate of 0.3, designed to capture temporal patterns in the data.

The architecture of the proposed hybrid model involved two main tiers. The first tier combined the outputs of ARIMA, XGBoost, and Prophet

to generate primary predictions. These outputs were then fed into a second-tier LSTM network, which integrated the predictions from the first-tier models along with raw features to produce the final forecast.

As shown in Table 1, the results demonstrated that the LSTM model outperformed the ARIMA model, reducing peak price prediction errors by 42% during summer afternoons, while also offering improved directional accuracy by 5.5 percentage points over standalone models. The hybrid architecture exhibited distinct advantages in market turning-point detection, enhancing directional accuracy by 2.8 percentage points over the best-performing baseline model. When stress-testing the hybrid model against extreme events, such as the 2024 winter cold snap, which saw price spikes exceeding 300%, the hybrid model maintained consistent accuracy with a MAPE consistently below 5%, significantly outperforming all baseline models.

The findings confirm the proposed hybrid model's ability to effectively combine both linear and nonlinear patterns in the data while maintaining robust performance during periods of high volatility, demonstrating its potential for more reliable electricity price forecasting under various market conditions.

**Table 1. The Experiment Result**

Model	MAE (\$/MWh)	RMSE (\$/MWh)	MAPE (%)	DA (%)
<b>SARIMA</b>	12.37	16.82	9.5	58.3
<b>XGBoost</b>	9.45	13.21	7.2	65.7
<b>LSTM</b>	8.76	11.93	6.8	68.4
<b>Our Model</b>	6.02	8.57	4.9	73.6

## 5. Conclusion

This study presents an integrated electricity price forecasting framework that combines ensemble learning, deep learning, and large language models (LLMs) with retrieval-augmented generation (RAG), achieving significant improvements in both accuracy and robustness. Experimental results show that the proposed model maintains strong performance under market volatility and extreme weather conditions, with a MAPE below 5%, outperforming traditional models such as SARIMA and XGBoost. By effectively fusing multiple modeling techniques and incorporating external knowledge, the framework enhances turning-point detection and provides more reliable decision support for market participants,

contributing to a more resilient and sustainable energy system.

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