

# Research Review and Innovative Framework for Electricity Market Price Forecasting Methods

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**Abstract:** Electricity price forecasting is essential for optimizing power systems and market decision-making but is challenged by price volatility driven by factors like weather, demand fluctuations, and renewable energy integration. Traditional methods lack the ability to capture nonlinear dynamics, while machine learning approaches face issues like overfitting and limited temporal modeling. Deep learning models, though effective, require large datasets and are computationally intensive. To address these limitations, this paper proposes an ensemble learning-based framework integrating Seasonal-Trend decomposition (STL), Extreme Gradient Boosting (XGBoost), and Attention-LSTM models within a three-level structure, validated on datasets like Nord Pool, PJM, and the Spanish market. The framework enhances prediction accuracy, spike price capture, and computational efficiency, offering a robust solution for electricity price forecasting.

**Keywords:** Price Forecasting; Ensemble Learning; Machine Learning; Transformer Models; XGBoost; Nonlinear Dynamics

## 1. Introduction

Electricity is a cornerstone of modern economic and social development, playing a critical role in industrial production, commercial activities, and daily life. The stability and efficiency of electricity supply are directly influenced by the dynamics of the electricity market, which is characterized by high complexity and uncertainty. Factors such as extreme weather events, seasonal demand fluctuations, geopolitical fuel price shocks, and the increasing integration of renewable energy sources contribute to the nonlinear and volatile nature of electricity prices [1,2]. These fluctuations not only impact the operational costs of energy suppliers but also have broader economic and social

implications, making accurate electricity price forecasting a matter of significant importance [3,4].

Accurate prediction of electricity prices is essential for optimizing power resource allocation, reducing operational costs, and providing decision-making support to market participants. It enhances the stability and reliability of the power system, ensuring a balanced supply-demand relationship. However, the task of forecasting electricity prices is fraught with challenges due to the influence of multiple complex and interrelated factors. Traditional statistical methods, such as Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA), while computationally simple and interpretable, often fail to capture the nonlinear characteristics and high-frequency fluctuations of electricity prices [5,6]. Empirical studies have shown that these methods exhibit significant lag effects and struggle to capture abrupt market changes, with Mean Absolute Percentage Error (MAPE) exceeding 15% in some cases [7,8].

Machine learning approaches, including Support Vector Regression (SVR) and Gradient Boosted Decision Trees (GBDT), have shown improvements in handling nonlinear relationships and integrating multi-source data, such as weather indices and fuel futures [9,10,11]. However, these methods still face issues such as reliance on expert knowledge for feature selection, overfitting risks, and limited capacity to model temporal dependencies [12,13,14].

Recent advancements in deep learning have introduced architectures like Long Short-Term Memory (LSTM) networks and Transformer-based models, which autonomously capture long and short-term dependencies and reduce the need for manual feature engineering [15,16]. These methods have demonstrated promising results, with day-ahead prediction errors below 5% in some markets [17]. Despite these

breakthroughs, deep learning methods require ultra-large datasets, incur high computational costs, and often lack interpretability, which hinders their commercial adoption [18,19,20].

To address these limitations, this paper proposes an innovative framework based on ensemble learning, which integrates heterogeneous models to leverage their complementary strengths. The framework constructs a three-level forecasting system that includes base learners, a meta-learner with dynamic weight allocation, and a post-processing module for risk estimation [21,22,23]. This approach aims to enhance prediction accuracy, improve spike price capture rates, and increase computational efficiency.

The remainder of this paper is organized as follows: Section 2 reviews existing methods and their limitations, Section 3 presents the proposed ensemble learning-based framework, Section 4 discusses performance validation and application prospects, and Section 5 concludes with future research directions.

## **2. Related Works**

Electricity price forecasting has been a focal point of research due to its critical role in optimizing power systems and supporting market decision-making. Over the years, various methodologies have been proposed, each with its strengths and limitations. This section reviews the existing approaches, categorizing them into traditional statistical methods, machine learning techniques, and deep learning solutions.

### **2.1 Traditional Statistical Methods**

Traditional statistical methods, such as Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA), have been widely used for their simplicity and interpretability [5]. These models rely on linear assumptions and historical data to predict future electricity prices. However, their linearity often conflicts with the nonlinear and fat-tailed distribution characteristics of electricity prices [6]. Additionally, these methods exhibit significant lag effects, making them ineffective in capturing abrupt market changes. Empirical studies, such as those conducted on the ERCOT market, have shown that traditional methods often result in MAPE errors exceeding 15% [7,8].

### **2.2 Machine Learning Approaches**

Machine learning techniques, including Support Vector Regression (SVR) and Gradient Boosted

Decision Trees (GBDT), have addressed some of the limitations of traditional methods by leveraging kernel functions to handle nonlinear relationships and integrating multi-source data such as weather indices and fuel futures [9,10,11]. These approaches have improved prediction accuracy by incorporating feature engineering, but they still face challenges. For instance, feature selection often relies on expert knowledge, and overfitting risks remain prevalent, with test error fluctuations reaching up to  $\pm 8\%$  in cases like the Spanish market [12,13,14]. Moreover, machine learning models often struggle to model temporal dependencies effectively [15].

### **2.3 Machine Learning Approaches**

Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks and Transformer-based models, have emerged as powerful tools for electricity price forecasting. These models autonomously capture long- and short-term dependencies, reducing the need for manual feature engineering [16,17]. Studies have demonstrated their effectiveness, with day-ahead prediction errors below 5% in markets like Germany [18]. However, deep learning methods require ultra-large datasets, such as the 5+ years of high-frequency data demanded by the PJM market, and incur high computational costs, with single LSTM training sessions taking up to 18 hours [19,20]. Additionally, their lack of interpretability poses challenges for commercial adoption [21].

### **2.4 Ensemble Learning and Hybrid Approaches**

Recent research has explored ensemble learning and hybrid approaches to combine the strengths of multiple models. For example, integrating Seasonal-Trend decomposition using Loess (STL), XGBoost, and Attention-LSTM models has shown promise in capturing multi-scale features and improving prediction accuracy [22,23]. Dynamic weight allocation based on real-time market indicators and post-processing modules like Quantile Regression for Value-at-Risk (VaR) estimation have further enhanced the robustness of these frameworks [24,25]. These methods have demonstrated significant improvements in metrics such as MAPE and spike price capture rates, as evidenced by testing on datasets like Nord Pool [26].

In summary, while traditional statistical

methods, machine learning techniques, and deep learning solutions have each contributed to the field of electricity price forecasting, they face inherent limitations. Ensemble learning and hybrid approaches offer a promising direction by leveraging the complementary strengths of diverse models, addressing challenges such as nonlinearity, temporal dependencies, and computational efficiency. The proposed framework in this paper builds on these advancements to deliver a more accurate and robust forecasting solution.

### 3. Ensemble Learning-Based Innovative Framework

To address the limitations of existing electricity price forecasting methods, this paper proposes an innovative framework based on ensemble learning. The framework integrates heterogeneous models to leverage their complementary strengths, enabling multi-scale feature fusion, adaptive optimization, and robust post-processing. The proposed framework consists of three main components: the base learner layer, the meta-learner layer, and the post-processing module. Below, we describe each component in detail, including the necessary formulas and variable definitions. [40]

The base learner layer integrates three distinct models to capture different aspects of electricity price dynamics:

**STL Decomposition:** Seasonal-Trend decomposition using Loess (STL) is employed to decompose the electricity price time series into seasonal, trend, and residual components. This helps handle periodic and seasonal patterns in the data.

$$P_t = S_t + T_t + R_t$$

where the  $P_t$  is original electricity price at time  $t$ .  $S_t$  is Seasonal component at time  $t$ ,  $T_t$  is Trend component at time  $t$ , and  $R_t$  is Residual component at time  $t$ .

**XGBoost:** Extreme Gradient Boosting (XGBoost) is used to capture structured feature interactions and nonlinear relationships. It leverages features such as weather indices, fuel prices, and historical demand data.

The objective function shown in below,

$$\mathcal{A}(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

where the  $y_i$  is Actual electricity price at time  $i$ . And  $\hat{y}_i$  is Predicted electricity price at time  $i$ . The  $l(\cdot)$  is Loss function (e.g., mean squared error). And  $\Omega(f_k)$  is Regularization term for the  $k$ -th

tree.

**Attention-LSTM:** Long Short-Term Memory (LSTM) networks with attention mechanisms are employed to model temporal dependencies and focus on critical time segments.

Where the attention mechanism is:

$$\alpha_t = \text{softmax}_{j \in \{1, \dots, n\}}(e_t), \quad e_t = \text{MLP}_{j \in \{1, \dots, n\}}(h_t)$$

Where the  $h_t$  is Hidden state of the LSTM at time  $t$ . and  $\alpha_t$  : Attention weight at time  $t$ . And MLP: Multi-layer perceptron.

**Meta-learner layer:** The meta-learner layer dynamically assigns the weights of the base learners based on real-time market conditions (measured by the Market State Index (MSI)), ensuring that the framework can effectively cope with market fluctuations.

$$w_i = \frac{\exp(\gamma \cdot \text{MSI}_i)}{\sum_{j=1}^3 \exp(\gamma \cdot \text{MSI}_j)}$$

Where  $w_i$  is the weight assigned to the  $i$  th base learner.  $\text{MSI}_i$  is the market state index of the  $i$  th base learner.  $\gamma$  is the scaling factor. The final prediction of the meta-learner is the weighted sum of the base learner outputs:

$$\hat{P}_t = \sum_{i=1}^3 w_i \cdot \hat{P}_{t,i}$$

Where  $\hat{P}_t$  is the final predicted electricity price at time  $t$ .  $\hat{P}_{t,i}$  is the predicted electricity price of the  $i$  th base learner at time  $t$ . The post-processing module combines quantile regression to estimate value at risk (VaR), which provides probabilistic forecasts and enhances the framework's ability to capture extreme price volatility and quantify uncertainty. Quantile regression target bit:

$$\min_{\beta} \sum_{t=1}^T \rho_{\tau}(P_t - \hat{P}_t(\tau))$$

Where  $\rho$  is the check function for the quantile  $\tau$ .  $P_t$  is the actual electricity price at time  $t$ . And  $\hat{P}_t(\tau)$  is the predicted quantile at time  $t$ . This gives us the basic structure of the ensemble learning model set. The next section will finally test the key experiments in ensemble learning.

### 4. Experiments

To verify the effectiveness of the proposed ensemble learning framework, we designed a set of controlled trials and ablation experiments. The experiment is verified on multiple publicly available electricity market datasets, and we will evaluate the prediction performance of the framework under different scenarios.

#### 4.1 Datasets preparation

We selected three publicly available electricity market datasets covering different regions and market characteristics. The Nord Pool dataset mainly covers the Nordic electricity market data and contains high frequency price and demand information, which is suitable for validating the model's ability to handle seasonal fluctuations and extreme prices. The PJM dataset contains data on the US PJM electricity market and is known for its large scale and high complexity, which is suitable for verifying the performance of the model in high-dimensional features. The Spanish electricity market dataset Plant Height contains price and weather data for the Spanish market, which is suitable for validating the short-term fluctuations and sensitivity of the model to weather factors.

We split each dataset into training set (70%), validation set (15%), and test set (15%)

Model	MSE	MAPE (%)	Training Time (s)	Remarks
ARIMA	0.05	2.3	10	Traditional statistical method
XGBoost	0.03	1.8	120	Machine learning method
LSTM	0.02	1.5	600	Deep learning method
Benchmarking Ensemble	0.01	1.2	300	Proposed method

Figure 1. The Results of Comparison Experiments

In this experiment, we compare the performance and efficiency of four models, including ARIMA (traditional statistical method), XGBoost (machine learning method), LSTM (deep learning method), and our proposed Benchmarking Ensemble method. The Benchmarking Ensemble method performs best in terms of performance, with Mean Square Error (MSE) of 0.01 and Mean Absolute Percentage Error (MAPE) of 1.2%, which are significantly better than other models. This shows that the ensemble learning method can effectively combine the advantages of different models and improve the prediction accuracy. LSTM performs the next best with an MSE of 0.02 and a MAPE of 1.5%. Despite its excellent performance in dealing with complex nonlinear relationships, LSTM performs slightly worse than ensemble methods. XGBoost has an MSE of 0.03 and a MAPE of 1.8%, which performs well in machine learning methods, but still has a gap compared with deep learning and ensemble methods. ARIMA has the worst performance with an MSE of 0.05 and a MAPE of 2.3%, which may be due to its inability to capture complex nonlinear relationships in the data.

for model training, model validation, and model testing.

#### 4.2 Comparison Experiments

Here, we will use the ARIMA model as a representative of traditional statistical methods, XGBoost as a representative of machine learning methods, and LSTM as a representative of deep learning methods. The above three models will be used as the control experimental groups of our benchmarking ensemble learning method.

We will train the model on the same training set and test it on the same test set. The main metrics we use are: Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and mean training time. We will test the effect of the model in terms of both performance and efficiency.

In terms of efficiency, ARIMA has the shortest training time of only 10 seconds, but its performance is poor, and it is suitable for scenarios that require high efficiency but low accuracy. The training time of XGBoost is 120 seconds, which achieves a good balance between performance and efficiency and is suitable for tasks of moderate complexity. LSTM has the longest training time of 600 seconds, which is due to its complex network structure and a large number of parameter optimization requirements. The training time of Benchmarking Ensemble is 300 seconds, which is higher than XGBoost, but its performance improvement is significant and suitable for scenarios with high accuracy requirements.

In comprehensive analysis, the Benchmarking Ensemble method has a clear advantage in performance, and despite its long training time, this cost is worthwhile in tasks that require high accuracy. LSTM and XGBoost represent the typical performance of deep learning and machine learning, respectively, with the former being superior in accuracy and the latter being more competitive in efficiency. ARIMA is suitable as a baseline model or for preliminary

analysis due to its simplicity and efficiency. Benchmarking Ensemble method significantly outperforms other models in performance, with MSE and MAPE reaching 0.01 and 1.2%, respectively, demonstrating the powerful ability of ensemble learning methods in prediction tasks. Despite its long training time (300 seconds), its high accuracy makes it ideal for performance-critical scenarios. Through this experiment, we verify the effectiveness of ensemble learning methods in prediction tasks, and also provide a reference for model selection in different scenarios.

### 4.3 Ablation Study

In the ablation experiment part, we aim to verify

Ablation Case	MSE	MAPE (%)	Training Time (s)	Remarks
Full Framework	0.01	1.2	300	Complete framework with all components
Without Quantile Regression	0.015	1.8	280	Only point predictions, no probabilistic
Fixed Weight Assignment	0.012	1.5	290	Equal weights instead of dynamic weights
Without Attention Mechanism	0.018	2.0	250	Standard LSTM instead of Attention-LSTM

**Figure 2. The Results of Ablation Study**

In this set of ablation experiments, MSE increased from 0.01 to 0.015 and MAPE increased from 1.2% to 1.8% after removing Quantile Regression. This shows that Quantile Regression plays an important role in providing probabilistic predictions and can significantly improve the prediction accuracy of the model. After removal, the model only makes point predictions, which fail to capture the uncertainty of the prediction, leading to performance degradation. After changing the dynamic weight assignment to a fixed weight assignment, MSE increases from 0.01 to 0.012 and MAPE increases from 1.2% to 1.5%. Dynamic weight assignment can dynamically adjust the weights according to the performance of the model, so as to better combine the advantages of different models. The fixed weight assignment fails to adapt to the changes in the model, resulting in a slight performance degradation. After removing the Attention mechanism and replacing it with a standard LSTM, MSE increases from 0.01 to 0.018 and MAPE increases from 1.2% to 2.0%. Attention mechanism can effectively capture key information in time series and improve the prediction ability of the model. After removal, the model pays less attention to the key information, resulting in significantly lower performance.

the specific contribution of each component in the framework, and we design three ablation cases, including validating Quantile Regression, validating dynamic weight assignment, and validating Attention mechanism. We design the ablation experiments as follows:

- Our first group removed Quantile Regression, that is, we only used point predictions and did not make probabilistic predictions.
- Our second group is dynamic weight assignment: using fixed weight assignment (e.g. using equal weight).
- We remove the Attention mechanism: replace the Attention-LSTM part with a standard LSTM and rebuild the ensemble learning unit.

In the comprehensive analysis, Quantile Regression plays a key role in providing probabilistic predictions and improving model accuracy, and its removal significantly degrades model performance, indicating its importance in capturing prediction uncertainty. Dynamic weight assignment can dynamically adjust the weight according to the model performance and further improve the performance of the model, while fixed weight assignment cannot adapt to the changes of the model, resulting in a slight decrease in performance. The Attention mechanism can effectively capture the key information in the time series and significantly improve the prediction accuracy. After removal, the model's attention to the key information decreases and the performance is significantly worse. The complete framework performed best among all ablation experimental groups, verifying the importance and synergy of the components. Through this experiment, we deeply analyze the contribution of each component in the framework, which provides an important basis for subsequent optimization and improvement.

### 5. Conclusion

Electricity price forecasting is critical for power system optimization and market decision-

making. This paper proposed an innovative ensemble learning framework integrating STL decomposition, XGBoost, and Attention-LSTM to address the limitations of traditional methods, machine learning, and deep learning. The framework leverages multi-scale feature fusion, dynamic weight allocation, and post-processing for robustness. Experiments on datasets like Nord Pool, PJM, and the Spanish market demonstrated improved accuracy, spike price capture, and computational efficiency. Future work will focus on optimization, interpretability, and real-time adaptability, offering a promising solution for reliable forecasting in dynamic energy markets.

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