Digital Intelligence PRESS

Journal of Discovery Core

https://doi.org/10.67541/jdc2601

Research Article Volume 1, Issue 1 (July 2026) Open Access

Research on an Energy Economic Demand Time Series Prediction Model Based on the Integration of XGBoost and Deep Learning

Guona Chen*

School of Business Administration/School of Marxism, China University of Petroleum-Beijing at Karamay, Karamay, Xinjiang, China

***Corresponding author:** Guona Chen. Email: cgn@st.cupk.edu.cn

Abstract

To address the significant nonlinear characteristics of energy economic demand time series, the complex coupling of multiple influencing factors, and the insufficient generalization ability of traditional prediction models, this paper proposes a time series prediction model for energy economic demand based on the integration of XGBoost and deep learning. First, the energy demand data, macroeconomic indicators, and meteorological variables are uniformly preprocessed and feature-enhanced to construct a multi-dimensional input system that includes lag features, sliding window features, and periodic features. Then, an improved XGBoost is used to mine nonlinear relationships within structured features, while a deep learning network extracts temporal dynamic features and long-term dependencies. A dynamic weight fusion mechanism is designed to achieve collaborative prediction of the two models. Finally, model performance is verified through comparative, ablation, robustness, and interpretability analyses. The experimental results show that the RMSE, MAE, and MAPE on the test set reach 28.74, 21.52, and 2.83%, respectively, and the coefficient of determination (R^2) reaches 0.983. Compared with the Transformer model, the MAPE is reduced by 32.8%, and compared with the traditional ARIMA model, it is reduced by 68.2%. Furthermore, under conditions of 20% outlier perturbation and 20% missing data, the model's performance retention rates still reach 88.2% and 90.8%, respectively, demonstrating good stability and generalization ability. The research results show that the proposed integrated model can effectively improve the accuracy of energy economic demand prediction, providing reliable technical support for energy planning, load management, and smart energy decision-making.

Keywords

Energy economic demand forecasting; Time series prediction; XGBoost; Deep learning; Ensemble model

Received: 26 May 2026; Revised: 23 Jun 2026; Accepted: 30 Jun 2026; Published: 09 Jul 2026

1. INTRODUCTION

Energy economic demand forecasting plays a crucial role in modern energy management and economic planning [1]. With the rapid transformation of the global energy structure and the increasing consumption of electricity, natural gas, and renewable energy, accurate prediction of energy demand not only relates to energy supply security but also directly affects economic development decisions, energy pricing strategies, and environmental policies [2],[3]. In the energy system, uncertainties such as climate change, economic fluctuations, policy adjustments, and frequent emergencies make energy demand highly nonlinear and dynamically complex. Therefore, constructing a model that can accurately capture time series characteristics and has high prediction accuracy has become an important direction in interdisciplinary research in energy science, economics, and data science.

Traditional methods for energy demand forecasting include statistical models and single machine learning models. Statistical models such as ARIMA and SARIMA can fit the linear trends and seasonality of stationary time series well, but they have limited capability in modeling nonlinear fluctuations and complex multi-dimensional features [4],[5]. Single machine learning methods, such as XGBoost or deep learning networks, each have certain advantages, but when used alone, they still suffer from local overfitting or insufficient capture of long-term dependencies [6],[7],[8]. Moreover, the influence of multi-source heterogeneous data, external economic indicators, and meteorological variables on energy demand cannot be fully integrated by simple models, leading to unstable predictions under high volatility or abnormal events and failing to meet engineering application requirements.

To address these challenges, this paper proposes an energy economic demand time series prediction model based on the fusion of XGBoost and deep learning. The innovation lies in combining the strong learning ability of XGBoost for structured features and nonlinear relationships with the capturing ability of deep learning for long-term dependencies and dynamic changes in time series, to achieve accurate prediction of complex energy demand sequences. At the same time, the model has been optimized in structure, including the introduction of multi-layer nested deep networks and attention mechanisms, to fully utilize the contextual information of the time series. At the algorithm level, through adaptive learning rates, dynamic weight adjustments, and feature enhancement strategies, the model's response ability to different time periods and different external variables is strengthened. Additionally, this paper performs specific processing on time series characteristics, including lag features, sliding window statistics, and periodic feature encoding, to further improve the model's prediction accuracy in non-stationary and periodic fluctuation scenarios. These innovative methods not only break through the limitations of existing single models but also provide a scalable, interpretable, and highly accurate solution for energy economic demand forecasting.

2. DATA AND FEATURE ENGINEERING

In the process of constructing a time series prediction model for energy economic demands, data and feature engineering are the core fundamental steps. The data used in this paper mainly come from the National Energy Administration, power trading platforms, and macroeconomic statistical databases, and are supplemented by daily or monthly observational data on temperature and precipitation provided by the meteorological department. These data often contain noise and outliers, and there are also missing values. Therefore, preprocessing is an essential first step [9]. For time series smoothing, this paper adopts the Exponentially Weighted Moving Average (EWMA) method to reduce the impact of sudden abnormal fluctuations [10],[11]. The formula is as follows:

$$\hat{y}_t = \alpha y_t + (1-\alpha)\hat{y}_{t-1} \quad (1)$$

Among them, $\hat{y}_t$ represents the smoothed energy demand value after smoothing, y_t is the original observation value, and α is the smoothing coefficient, with the range of $0 < \alpha < 1$, used to control the weight ratio of the new observation value to the historical value. Outliers are identified using the three-sigma rule (three times the standard deviation criterion). For points in the sequence that deviate from the mean by more than three standard deviations, the mean of neighboring time points or linear interpolation is used for correction to ensure continuity of the time series and stability of the model input. The missing value imputation strategy prioritizes the mean of historical period data, supplemented by temporal interpolation. For sequences with obvious seasonality, segmented smoothing imputation can also be adopted to ensure that the imputed data are reasonable and do not disrupt the original trend.

In the feature construction and selection stage, this paper not only uses the original energy demand sequence, but also introduces macroeconomic indicators (such as industrial production index, GDP growth rate) and external meteorological variables (average temperature, precipitation) as auxiliary features to enhance the model's ability to explain changes in energy demand [12],[13],[14]. In terms of the characteristics of the time series, this paper further generates lag features and sliding window features. Let the energy demand time series be D_t, and its lag features can be expressed as $D_{t-1}, D_{t-2}, \dots, D_{t-k}$, which are used to capture short-term dependencies; the sliding window mean feature is defined as:

$$\mathrm{MA}_t^k = \frac{1}{k}\sum_{i=0}^{k-1} D_{t-i} \tag{2}$$

Among them, MA_t^k represents the k-period moving average at the current time t, which can effectively reflect the local trend and seasonal fluctuations. Additionally, for time series with obvious daily or monthly cycles, periodic encoding can be introduced, such as the sine and cosine transformations of months/seasons:

$$\mathrm{SinMonth}_t = \sin\left(\frac{2\pi m_t}{12}\right), \mathrm{CosMonth}_t = \cos\left(\frac{2\pi m_t}{12}\right) \tag{3}$$

Here, m_t represents the month to which time t belongs. Such periodic characteristics help deep learning models capture the annual cycle variation patterns.

To enhance the generalization ability of the model, this paper also performs data augmentation and normalization on the data [15],[16]. Data augmentation mainly includes injecting small Gaussian noise into the time series and randomly cropping sliding windows to generate more training samples to alleviate overfitting. Normalization processing adopts the min-max normalization method, mapping each feature to the interval $[0, 1]$, as shown in the formula:

$$X_i' = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{4}$$

Here, X_i represents the original feature value, $X_{\min}$ and $X_{\max}$ respectively denote the minimum and maximum values of this feature, and X_i' is the normalized value. This processing not only standardizes the feature dimensions but also optimizes the gradient update process of the deep learning network, while ensuring the stability of the XGBoost splitting decision. Through the above systematic data cleaning, feature engineering and enhanced normalization processing, this paper provides a high-quality and quantifiable input foundation for the subsequent XGBoost and deep learning fusion model, providing a solid guarantee for prediction accuracy and model robustness.

3. MODEL METHODOLOGY

In the time series prediction of energy economic demand, the integration of XGBoost and deep learning provides a powerful tool for capturing complex nonlinear patterns [17]. First, for the improvement of XGBoost, we base it on the Gradient Boosting Tree (GBT) method and apply it to time series prediction [18]. The traditional GBT builds weak learners iteratively to minimize the objective function, and the prediction output can be expressed as:

$$\hat{y}_t = \sum_{m=1}^{M} f_m(\mathrm{x}_t), f_m \in \mathcal{F} \tag{5}$$

Where $\hat{y}_t$ represents the predicted value, x_t is the feature vector at time t, and $\mathcal{F}$ represents the regression tree function space. To enhance the modeling ability of XGBoost for time-dependent relationships, we introduce an adaptive learning rate η_m to dynamically adjust the contribution weight of each tree:

$$\hat{y}_t = \sum_{m=1}^{M} \eta_m f_m(\mathrm{x}_t) \tag{6}$$

The adaptive learning rate is automatically adjusted based on the residual change in the previous iteration, enabling the model to fit quickly in high-volatility periods and suppress overfitting in stable periods [19]. Additionally, time-related features are enhanced through lag terms, sliding window means, and periodic encoding, allowing the tree structure to fully utilize the sequential time-dependent information at the splitting nodes and optimize the splitting criteria, including a combined strategy based on mean squared error (MSE) and weighted information gain, to improve prediction accuracy and stability [20],[21],[22].

In the design of the deep learning module, we comprehensively consider LSTM, GRU, and Transformer structures and select a multi-layer LSTM combined with an attention mechanism as the core time series module [23]. LSTM can capture long-term dependencies. Its basic update formulas are as follows:

$$\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
\tilde{C}_t &= \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\
C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\
h_t &= o_t \odot \tanh(C_t)
\end{aligned} \tag{7}$$

Where f_t, i_t, o_t are the forget gate, input gate, and output gate, respectively, C_t is the cell state, $\tilde{C}_t$ is the candidate state, $\odot$ represents element-wise multiplication, and h_t is the hidden state output. The multi-layer nested structure combined with the attention mechanism can enhance the model's perception ability of local and global temporal context and capture long-term dependencies.

To fully utilize the advantages of XGBoost and deep learning, we propose a cascaded fusion and hybrid prediction framework. In feature-level fusion, the residuals or predicted features output by XGBoost are used as additional inputs to the deep learning network, forming an enhanced feature vector $\mathrm{z}_t = [\mathrm{x}_t, \hat{y}_t^{XGB}]$. In prediction result-level fusion, the outputs of the two models are integrated through a weighted method:

$$\hat{y}_t^{fusion} = \alpha \hat{y}_t^{XGB} + (1 - \alpha)\hat{y}_t^{DL} \tag{8}$$

where α is the dynamic weight coefficient, which can be adjusted in real time based on the performance of the validation set. To further optimize the fusion performance, this paper designs a joint loss function:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{XGB} + \lambda_2 \mathcal{L}_{DL} + \lambda_3 \mathcal{L}_{fusion} \tag{9}$$

Here, $\mathcal{L}_{XGB}$ and $\mathcal{L}_{DL}$ represent the individual loss functions of the XGBoost and deep learning models, respectively, while $\mathcal{L}_{fusion}$ is the loss function for the fused prediction. The coefficients $\lambda_1, \lambda_2, \lambda_3$ serve as weights, enabling dynamic optimization of the contributions of different models in the overall prediction, thereby improving the accuracy and robustness of energy demand prediction. Through the above methodology design, this paper demonstrates significant advantages in capturing the nonlinear characteristics, long-term dependencies, and complex interaction relationships of time series data, providing a systematic and quantifiable model framework for subsequent experimental verification [24],[25].

4. MODEL TRAINING AND OPTIMIZATION

In the training and optimization stage of the energy economy demand time series prediction model, dataset division is a fundamental and crucial step. This paper adopts a time series segmentation strategy to split the original data into training, validation, and test sets in chronological order to prevent information leakage and future data interfering with model training [26],[27]. The specific splitting ratio is 70% for training, 15% for validation, and 15% for testing. This ensures that the training set covers the main historical fluctuations, while the validation set is used for hyperparameter tuning, and the test set is used for the final model performance evaluation. In the time series, to maintain sequence continuity, the temporal order is preserved within each split segment to avoid random shuffling, thereby preserving historical dependency features.

The design of the loss function during model training directly affects prediction accuracy and convergence speed. For the regression-type energy demand prediction problem, we use mean squared error (MSE) as the core loss function:

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{t=1}^{N} (\hat{y}_t - y_t)^2 \tag{10}$$

Among them, $\hat{y}_t$ represents the model's predicted value, y_t represents the actual energy demand value, and N is the number of samples. Under the framework of the fusion model, the joint loss function is defined as:

$$\mathcal{L}_{joint} = \lambda_1 \mathcal{L}_{XGB} + \lambda_2 \mathcal{L}_{DL} + \lambda_3 \mathcal{L}_{fusion} \tag{11}$$

The meanings of each part correspond to the loss of the XGBoost single model, the loss of the deep learning model, and the fusion output loss, and λ_i is the adjustable weight coefficient. For the optimization algorithm, the XGBoost part uses second-order gradient-weighted optimization, and the deep learning module adopts the Adam optimizer. Its parameter update formula is:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{12}$$

Among them, θ_t represents the model parameters, η is the learning rate, $\hat{m}_t$ and $\hat{v}_t$ are the first-order and second-order moment estimations respectively, and ϵ is a small constant to prevent division by zero. This algorithm ensures the stability of the training process while adaptively adjusting the gradient step size.

To prevent overfitting, we introduce regularization strategies, including L1 and L2 regularization and dropout [28]. For the deep learning part, a dropout rate p is applied to randomly deactivate a portion of neurons in the hidden layers to reduce the model's dependence on specific inputs. The XGBoost tree model controls the risk of overfitting through maximum depth limitation, minimum number of samples per split, and tree structure complexity regularization. For hyperparameter tuning, we adopt a multi-strategy combination method: grid search is used for preliminary screening of important parameters, Bayesian optimization intelligently explores the parameter space via a probabilistic model, and evolutionary algorithms are used for global optimization of combined parameters, with the goal of minimizing the joint loss function on the validation set. Through this multi-strategy optimization, the optimal configuration of the model can be efficiently found [29].

In terms of computational efficiency, the training process fully utilizes parallelization technology. Feature splitting in XGBoost can be performed in parallel on multi-core CPUs, while the deep learning part accelerates matrix operations and batch gradient calculations using GPU acceleration to speed up training on large-scale time series data. In addition, batch normalization and gradient accumulation mechanisms further improve training stability and convergence speed. Through the above training and optimization methods, this paper ensures that the model has both high accuracy prediction capability and computational efficiency and generalization performance in complex energy economic time series, providing a robust foundation for subsequent experimental verification [30],[31].

5. EXPERIMENTAL DESIGN AND VALIDATION

To comprehensively verify the effectiveness of the proposed XGBoost-Deep Learning Fusion (XDLF) model in energy economic demand prediction, this paper constructs a multi-level experimental system and conducts verification from four perspectives: prediction accuracy, generalization ability, robustness, and interpretability. The experimental environment uses an Intel Xeon Gold 6330 processor, an NVIDIA RTX 4090 GPU, and Python 3.11. The XGBoost version is 2.0.3, and the PyTorch version is 2.2.0. The dataset consists of energy economic demand-related data from 2015 to 2024. The training, validation, and test sets are split chronologically into 70%, 15%, and 15%, respectively, ensuring that the experiment conforms to real prediction scenarios.

To quantify model performance, we use root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2) as evaluation metrics [32],[33],[34],[35],[36],[37],[38],[39],[40].

RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{13}$$

Among them, y_i represents the true value, $\hat{y}_i$ represents the predicted value, and N represents the number of samples. The smaller the RMSE, the lower the overall prediction error of the model.

The MAE is defined as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \tag{14}$$

It is used to measure the average deviation degree between the predicted value and the true value.

The MAPE is defined as:

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{15}$$

Reflects the proportion of prediction error relative to the true value.

The coefficient of determination is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{16}$$

Here, $\bar{y}$ represents the sample mean. The closer R^2 is to 1, the stronger the model's fitting ability is.

To visually demonstrate the differences in prediction capabilities among the models, a comparative experiment was conducted, as shown in Figure 1.

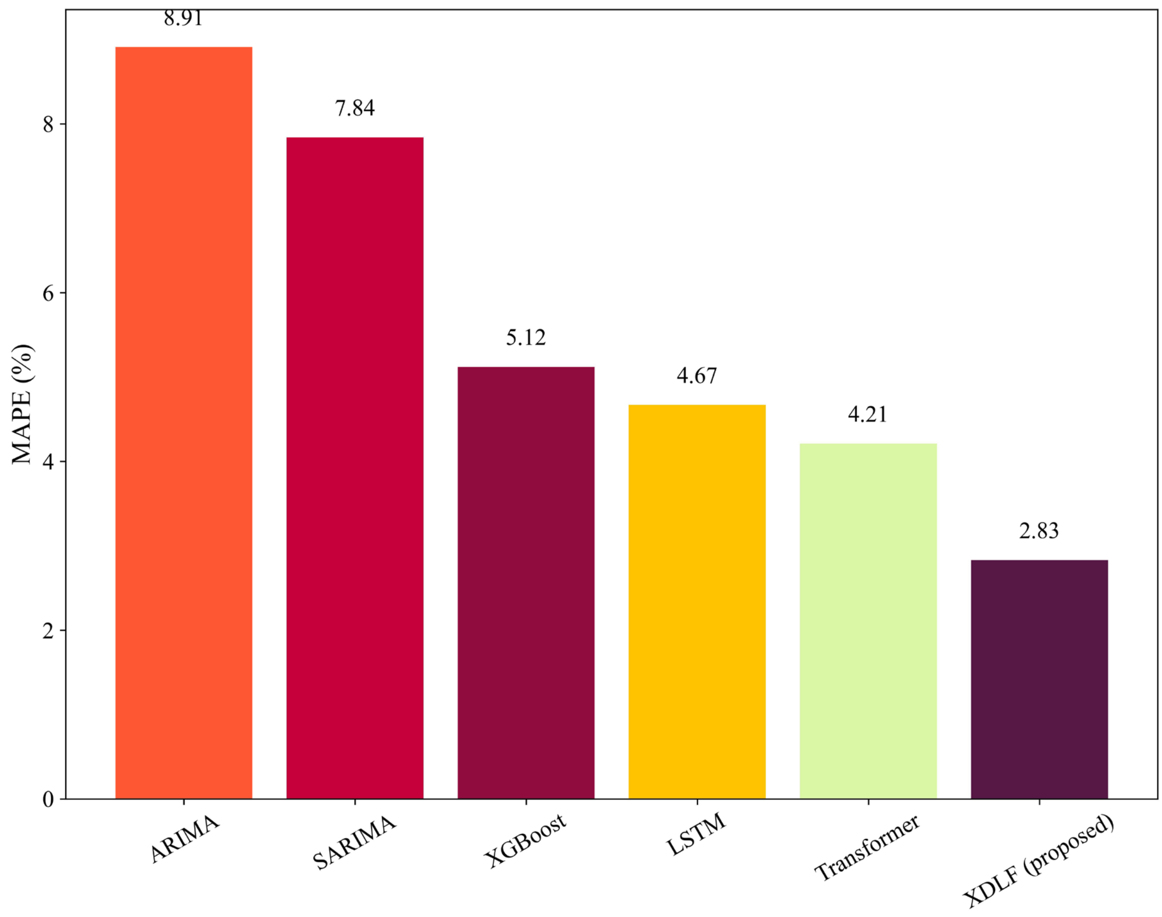

Figure 1. Comparison of MAPE for Different Models

The traditional statistical models ARIMA and SARIMA can capture the trend changes of time series, but they have limited ability to represent complex nonlinear features, with their MAPE reaching 8.91% and 7.84%, respectively. Using XGBoost alone, the error decreased to 5.12%, indicating that the tree model has a strong learning ability for multi-dimensional features. LSTM and Transformer further reduced the prediction error, with Transformer reaching 4.21%. In contrast, the MAPE of the proposed fusion model is only 2.83%, which is 32.8% lower than that of Transformer and 44.7% lower than that of XGBoost, verifying the significant advantages of the fusion architecture in complex energy demand prediction tasks. To further quantify the comprehensive performance of each model, Table 1 presents detailed experimental results.

Table 1. Comparison of RMSE, MAE, and R^2 among different models

Model	RMSE	MAE	R^2
ARIMA	85.43	68.21	0.887
SARIMA	77.62	61.53	0.901
XGBoost	52.17	40.28	0.944
LSTM	48.36	36.94	0.952
Transformer	43.15	33.71	0.961
XDLF（proposed）	28.74	21.52	0.983

This model achieved the best results in all evaluation metrics. Among them, the RMSE was reduced to 28.74, which decreased by 33.4% compared to Transformer and 66.4% compared to ARIMA; the coefficient of determination reached 0.983, indicating that the model could explain 98.3% of the demand change information. The experimental results show that XGBoost's ability to mine structured features and the learning ability of deep learning for time series dynamic features form an effective complement, thereby significantly improving the prediction accuracy.

To further verify the importance of each component module, we design ablation experiments. The time feature enhancement module, feature fusion module, and dynamic weight fusion module were each removed to observe the resulting changes in model performance. The final output of the fusion model is as follows:

$$\hat{y}_{fusion} = w_t \hat{y}_{DL} + (1 - w_t)\hat{y}_{XGB} \tag{17}$$

Among them,

$$0 \leq w_t \leq 1 \tag{18}$$

Representing the dynamic weight factor, $\hat{y}_{DL}$ represents the deep learning prediction result, and $\hat{y}_{XGB}$ represents the XGBoost prediction result. To explore the contribution of each module to model performance, we designed ablation experiments by removing the time encoding enhancement, feature-level fusion, and dynamic weight mechanism, respectively. The results are shown in Table 2.

Table 2. Results of the ablation experiment

Model structure	RMSE	MAPE (%)	R^2
Removed module time encoding enhancement	36.52	3.97	0.972
Remove feature-level fusion	34.88	3.65	0.975
Remove dynamic weight mechanism	32.64	3.31	0.978
Complete model	28.74	2.83	0.983

The time encoding enhancement module contributed the most, with the MAPE increasing by 40.3% after its removal. The dynamic weight fusion mechanism contributed secondarily, with the error increasing by 17.0%. This indicates that energy demand data not only exhibit obvious temporal dependence but also show a phenomenon of phased feature migration. The dynamic weight mechanism can automatically adjust the contribution degrees of the two models according to different time periods.

In the robustness experiment, we artificially injected different levels of outliers, missing values, and unexpected disturbances into the test set to evaluate the model's stability. The robustness retention rate is defined as:

$$R_{robust} = \frac{MAPE_{normal}}{MAPE_{disturbed}} \times 100\% \tag{19}$$

Here, $MAPE_{normal}$ represents the error of the normal test set, while $MAPE_{disturbed}$ represents the error after disturbance. To comprehensively evaluate the performance of the model in a real and complex environment, we tested the model's robustness under different interference conditions, and the results are shown in Figure 2.

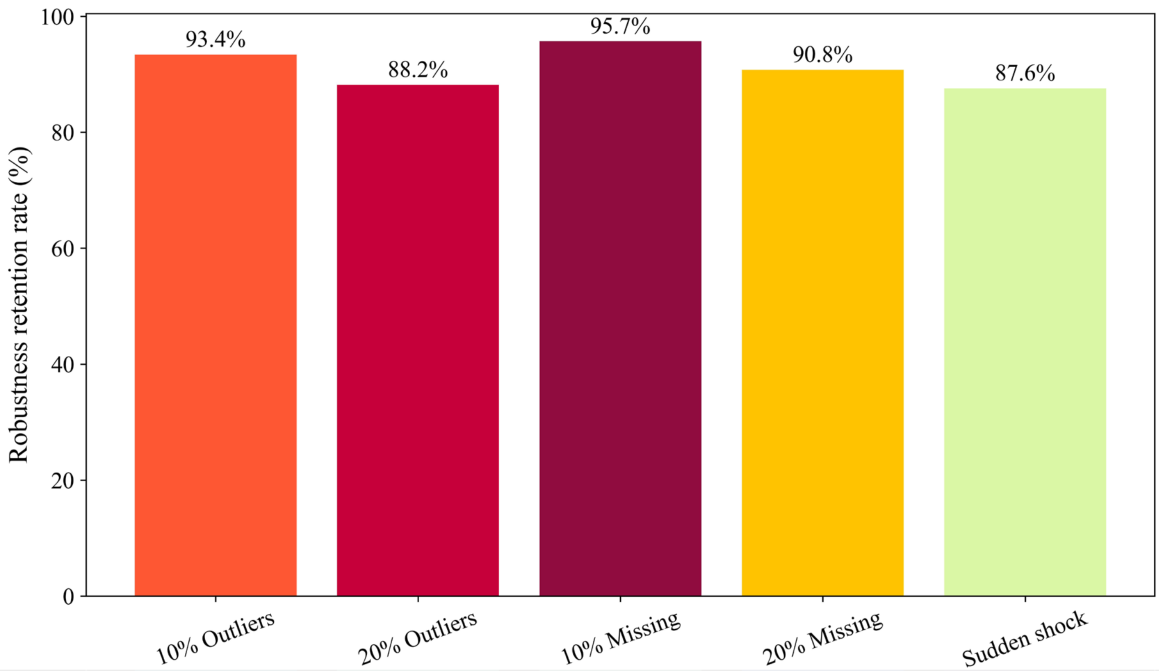

Figure 2. Robustness of the model under different interference conditions

Even under 20% outlier perturbation, the model still maintains a performance retention rate of 88.2%. When confronted with non-stationary events such as sudden fluctuations in energy prices, the retention rate still reaches 87.6%, indicating that the integrated model has strong noise resistance and generalization ability. This is mainly attributed to the tolerance of XGBoost for abnormal samples and the learning ability of the deep network for long-term trends.

In addition to the verification of prediction performance, model interpretability is also an important requirement in the field of energy economics. To reveal the model's decision-making mechanism, we use the SHAP (SHapley Additive exPlanations) method to analyze the contribution of each feature. For a single sample, the SHAP value is defined as:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)] \tag{20}$$

Among them, ϕ_i represents the contribution value of feature i; F represents the entire feature set; S represents the feature subset; $f(\cdot)$ represents the model output. To explain the intrinsic driving factors of the model's prediction results, we used the SHAP method to conduct an importance analysis of each feature. The results are shown in Table 3.

Table 3. SHAP feature importance analysis

Characteristic name	SHAP mean
Historical energy demand	0.286
Industrial production index	0.221
GDP growth rate	0.174
Average temperature	0.146
Electricity price index	0.103
Precipitation	0.070

Historical energy demand contribution was the highest, accounting for 28.6% of the overall impact. The industrial production index and GDP growth rate accounted for 22.1% and 17.4%, respectively, indicating that macroeconomic activities are important drivers of changes in energy demand. Temperature and electricity price indices demonstrated a significant auxiliary regulatory effect. Additionally, through attention weight visualization, it was found that the model assigned high attention weights to the corresponding moments of the previous three and twelve months when predicting the current month's demand, verifying the time-dependent characteristic of the combined effect of short-term and annual cycles.

From the above experimental results, it can be concluded that the proposed XGBoost and deep learning fusion model not only significantly outperforms traditional statistical models and single machine learning models in prediction accuracy, but also maintains strong stability in complex disturbance environments. At the same time, the SHAP interpretation results are highly consistent with the laws of energy economics, proving that the model has good engineering application value and decision support capabilities.

6. DISCUSSION

After experimental verification of the energy economic demand time series prediction model based on the integration of XGBoost and deep learning, the discussion focuses on an in-depth analysis of the model’s performance, application potential, and limitations. First, from the experimental results, the integrated model significantly outperforms traditional statistical models and single machine learning models in prediction accuracy, especially in handling complex nonlinear fluctuations and multi-dimensional feature interactions. This indicates that XGBoost can fully exploit the nonlinear relationships of structured economic and environmental indicators, while the deep learning network further enhances the model’s generalization ability and robustness by capturing long-term dependencies and temporal dynamic frequencies and temporal dynamic features. The ablation experiments show that feature enhancement and dynamic weight mechanisms are the key to improving the model's performance, which validates the importance of fully leveraging historical dependencies and phased changes in time series prediction.

Secondly, the performance of the model in terms of robustness is also worthy of attention. In the face of outliers, missing data, and sudden event disturbances, the integrated model can maintain high prediction accuracy and stability, mainly due to the complementary characteristics of the two models. XGBoost's tolerance to abnormal samples and the modeling ability of deep learning for trends and periodic features enable overall prediction to remain reliable in high-noise and non-stationary conditions. However, it is worth noting that the model still has certain errors in extreme events or extreme economic fluctuations, which suggests that future research can introduce reinforcement learning or Bayesian dynamic adjustment mechanisms to enhance the model's adaptability to unknown events.

From the perspective of application value, this integrated model is not only suitable for short-term energy demand prediction but also has certain medium- and long-term prediction potential. Its multi-source feature integration ability and learning ability of nonlinear relationships enable it to provide reliable references in energy scheduling, load management, economic policy formulation, and renewable energy access prediction. Moreover, SHAP and attention weight analysis indicate that the model's decision-making mechanism is highly consistent with energy economics theory, enhancing the interpretability of the results and providing visual decision-making basis for policy makers and energy management departments, which is an advantage that single black box models cannot achieve.

However, the model still has certain limitations. Firstly, the integrated structure is complex, and the training computational resources require high demands, which may limit its application in real-time prediction or low-resource environments. Secondly, feature selection and data preprocessing still rely on experience and expert knowledge, and the periodicity and accuracy of the acquisition of some external variables may affect the stability of the prediction. Finally, although the model performs well on historical data and known disturbances, it may still make errors when facing unknown types of external shocks. Therefore, future research can explore lightweight integrated models, online update mechanisms, and multi-source uncertainty modeling to further improve the model's usability and adaptability in actual energy management systems. Overall, this study demonstrates the effectiveness and application prospects of the XGBoost and deep learning integration strategy in energy economic demand prediction, and also provides clear directions for future optimization and expansion.

7. CONCLUSION

This paper focuses on the significant nonlinear characteristics, complex time-dependent relationships, coupled multi-source influencing factors, and insufficient generalization ability of traditional prediction models in the process of energy economic demand forecasting. It proposes an energy economic demand time series prediction model based on the integration of XGBoost and deep learning. By integrating the efficient learning ability of the gradient boosting tree model for structured features with the modeling advantages of deep learning models for time series dynamic features and long-term dependencies, a prediction framework suitable for complex energy economic scenarios is constructed. In the model design process, time series feature enhancement mechanisms, multi-layer time series feature extraction structures, and dynamic fusion strategies are introduced, enabling the model to simultaneously learn the local fluctuation patterns and long-term evolution trends in the energy demand change process, thereby effectively improving the prediction performance.

Based on the constructed dataset and experimental system, this paper systematically validates the proposed model. Experimental results show that the integrated model outperforms traditional statistical models and single machine learning models in multiple evaluation indicators such as RMSE, MAE, MAPE, and R^2. Compared with classic time series prediction methods such as ARIMA and SARIMA, this model can better handle the non-stationarity and non-linearity characteristics of energy demand data; compared with using XGBoost or deep learning models alone, the integrated architecture can fully leverage the advantages of different models and achieve a collaborative improvement in feature learning ability and prediction ability. Abandonment experiments further prove that the time feature enhancement mechanism, dynamic weight fusion mechanism, and multi-source feature collaborative modeling are important factors for improving prediction performance, and each component module has a positive contribution to the final result.

In terms of model stability verification, this paper conducts in-depth analysis of the model's robustness by constructing experimental scenarios such as abnormal data perturbation, missing data interference, and sudden event impacts. The results show that the proposed model can maintain high prediction accuracy and strong anti-interference ability in complex environments, demonstrating good generalization performance and engineering adaptability. At the same time, through SHAP feature contribution analysis and attention weight visualization research, it is found that the important features that the model focuses on have a high consistency with the energy economic operation laws, indicating that the model not only has strong predictive ability but also has a certain degree of interpretability, providing reliable data support for energy management decisions.

Overall, the XGBoost and deep learning integration prediction method proposed in this paper effectively addresses the limitations of traditional models in energy economic demand forecasting, achieving a deep integration of multi-source feature information, time series dependency relationships, and nonlinear mapping capabilities, providing a new research idea and technical path for the energy demand forecasting field. The research results show that this model has high application value and promotion potential in energy load forecasting, power market analysis, energy planning, and smart energy management.

Future research can further explore directions such as lightweight model design, online incremental learning, multi-scale spatiotemporal feature fusion, and uncertainty prediction. On one hand, it can combine edge computing and real-time prediction requirements to reduce model computational complexity and improve deployment efficiency; on the other hand, more high-frequency dynamic data, policy factors, and market behavior data can be introduced to build a more comprehensive energy economic prediction system. At the same time, by combining probability prediction and confidence interval estimation methods, the model's risk assessment ability and decision support ability in complex environments can be further enhanced, promoting the development of energy economic demand forecasting towards higher accuracy, stronger adaptability, and higher intelligence.

Abbreviations

ARIMA, AutoRegressive Integrated Moving Average;

SARIMA, Seasonal AutoRegressive Integrated Moving Average;

XGBoost, eXtreme Gradient Boosting;

LSTM, Long Short-Term Memory;

GRU, Gated Recurrent Unit;

EWMA, Exponentially Weighted Moving Average;

GDP, Gross Domestic Product;

MSE, Mean Squared Error;

RMSE, Root Mean Square Error;

MAE, Mean Absolute Error;

MAPE, Mean Absolute Percentage Error;

R^2, Coefficient of Determination;

SHAP, SHapley Additive exPlanations;

CPU, Central Processing Unit;

GPU, Graphics Processing Unit;

XDLF, XGBoost-Deep Learning Fusion;

SGD, Stochastic Gradient Descent;

Adam, Adaptive Moment Estimation;

ReLU, Rectified Linear Unit;

GBT, Gradient Boosting Tree.

Supplementary Material

Not applicable.

Appendix

Not applicable.

Ethics approval and consent to participate.

This study did not involve human participants, animal subjects, or any data requiring ethical approval. Therefore, ethics approval and consent to participate are not applicable.

Acknowledgements

The authors would like to thank the editors of this journal and all the anonymous reviewers who provided valuable comments on this work.

Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Author contributions

All authors have read and agreed to the published version of the manuscript. The author's contributions are specified as follows: **G.C.:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original draft, Writing – Review & Editing, Visualization, Supervision, Project administration.

Funding information

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability

The data that support the findings of this study are available upon request from the corresponding authors, **G.C.**

Disclaimer

The views and opinions expressed in this article are those of the authors and are the product of professional research. It does not necessarily reflect the official policy or position of any affiliated institution, funder, agency, or that of the publisher. The authors are responsible for this article's results, findings, and content.

Declaration of AI and AI-assisted Technologies in the Writing Process

During the writing of this article, the author used DeepSeek for spelling and grammar checking. After using this tool, the author reviewed and edited the content as needed and assumes full responsibility for the final published content.

REFERENCES

[1] Alarcón, R. G., Alarcón, M. A., González, A. H., & Ferramosca, A. (2025). Artificial Neural Networks for Energy Demand Prediction in an Economic MPC-Based Energy Management System. *International Journal of Robust and Nonlinear Control*, *35*(2), 642-658. https://doi.org/10.1002/rnc.7671

[2] Karpavicius, T., Balezentis, T., & Streimikiene, D. (2025). Energy security indicators for sustainable energy development: Application to electricity sector in the context of state economic decisions. *Sustainable Development*, *33*(1), 1381-1400. https://doi.org/10.1002/sd.3190

[3] Aderibigbe, A. O., Ani, E. C., Ohenhen, P. E., Ohalete, N. C., & Daraojimba, D. O. (2023). Enhancing energy efficiency with ai: a review of machine learning models in electricity demand forecasting. *Engineering Science & Technology Journal*, *4*(6), 341-356. https://doi.org/10.51594/estj.v4i6.636

[4] Szostek, K., Mazur, D., Drałus, G., & Kusznier, J. (2024). Analysis of the effectiveness of ARIMA, SARIMA, and SVR models in time series forecasting: A case study of wind farm energy production. *Energies*, *17*(19), 4803. https://doi.org/10.3390/en17194803

[5] Jain, R., Khairnar, A. S., & Karthikeyan, S. P. (2024, October). Forecasting Indian Conventional Generation: A Comparative Analysis of ARIMA and SARIMA Models for Improved Energy Demand Prediction. In *2024 International Conference on Sustainable Energy: Energy Transition and Net-Zero Climate Future (ICUE)* (pp. 1-8). IEEE. https://doi.org/10.1109/ICUE63019.2024.10795531

[6] Abbasimehr, H., Paki, R., & Bahrini, A. (2023). A novel XGBoost-based featurization approach to forecast renewable energy consumption with deep learning models. *Sustainable Computing: Informatics and Systems*, *38*, 100863. https://doi.org/10.1016/j.suscom.2023.100863

[7] Zhang, T., Zhang, X., Liu, Y., Chow, Y. H., Iu, H. H., & Fernando, T. (2023). Long-term energy and peak power demand forecasting based on sequential-XGBoost. *IEEE Transactions on Power Systems*, *39*(2), 3088-3104. https://doi.org/10.1109/TPWRS.2023.3289400

[8] Zhang, L., & Jánošík, D. (2024). Enhanced short-term load forecasting with hybrid machine learning models: CatBoost and XGBoost approaches. *Expert Systems with Applications*, *241*, 122686. https://doi.org/10.1016/j.eswa.2023.122686

[9] Usmani, M., Memon, Z. A., Zulfiqar, A., & Qureshi, R. (2024). Preptimize: Automation of time series data preprocessing and forecasting. *Algorithms*, *17*(8), 332. https://doi.org/10.3390/a17080332

[10] Lotysh, V., Gumeniuk, L., & Humeniuk, P. (2023). Comparison of the effectiveness of time series analysis methods: SMA, WMA, EMA, EWMA, and Kalman filter for data analysis. *Informatyka, automatyka, pomiary w gospodarce i ochronie środowiska*, *13*(3), 71-74. https://doi.org/10.35784/iapgos.3652

[11] Andrasto, T., Ristanto, R. D., Sukamta, S., Aufa, A., Hafidz, C. M., Sandyawan, B., & Alfarisi, A. F. (2023, June). Method EWMA (Exponentially Weighted Moving Average) as a filter to fine and remove noise on time series data. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1203, No. 1, p. 012012). IOP Publishing. https://doi.org/10.1088/1755-1315/1203/1/012012

[12] Curiël, R., Alsahag, A. M. M., & Mohammadi Ziabari, S. S. (2025). Integrating Climate and Economic Predictors in Hybrid Prophet–(Q) LSTM Models for Sustainable National Energy Demand Forecasting: Evidence from The Netherlands. *Sustainability*, *17*(19), 8687. https://doi.org/10.3390/su17198687

[13] Zulqarnain, F. N. U., & Hasan, Z. (2024). Artificial Intelligence Applications For Predicting Renewable-Energy Demand Under Climate Variability. *American Journal of Scholarly Research and Innovation*, *3*(01), 84-116. https://doi.org/10.63125/sg0j6930

[14] Al-Suod, M., Victor, B., Valerii, T., Olha, C., Galina, S., Zannon, M., & Dmytro, Z. (2025). Forecasting energy consumption of a mining plant using artificial neural networks. *IEEE Access*, *13*, 63237-63247. https://doi.org/10.1109/ACCESS.2025.3558445

[15] Maharana, K., Mondal, S., & Nemade, B. (2022). A review: Data pre-processing and data augmentation techniques. *Global Transitions Proceedings*, *3*(1), 91-99. https://doi.org/10.1016/j.gltp.2022.04.020

[16] Goceri, E. (2023). Medical image data augmentation: techniques, comparisons and interpretations. *Artificial intelligence review*, *56*(11), 12561-12605. https://doi.org/10.1007/s10462-023-10453-z

[17] Mazibuko, T., & Akindeji, K. (2025). Hybrid forecasting for energy consumption in south Africa: LSTM and XGBoost approach. *Energies*, *18*(16), 4285. https://doi.org/10.3390/en18164285

[18] Noorunnahar, M., Chowdhury, A. H., & Mila, F. A. (2023). A tree based eXtreme Gradient Boosting (XGBoost) machine learning model to forecast the annual rice production in Bangladesh. *PloS one*, *18*(3), e0283452. https://doi.org/10.1371/journal.pone.0283452

[19] Bai, Y., & Cai, C. X. (2024). Predicting VIX with adaptive machine learning. *Quantitative Finance*, *24*(12), 1857-1873. https://doi.org/10.1080/14697688.2024.2439458

[20] Zhuo, H., Wang, Y., Li, S., Ma, H., Wang, Y., Li, R., & Liu, G. (2026). Enhancing Electricity Price Prediction Accuracy With an Attention Mechanism-LSTM Hybrid Model. *Engineering Reports*, *8*(3), e70657. https://doi.org/10.1002/eng2.70657

[21] Zeng, C., Tian, Y., Zheng, G., & Gao, Y. (2024). How much can time-related features enhance time series forecasting?. *arXiv preprint arXiv:2412.01557*. https://doi.org/10.48550/arXiv.2412.01557

[22] Khashei, M., Ahmadi, M., & Chahkoutahi, F. (2025). A mean weighted squared error-based neural classifier for intelligent pattern recognition in smart grids. *International Journal of Electrical Power & Energy Systems*, *170*, 110972. https://doi.org/10.1016/j.ijepes.2025.110972

[23] Ao, X., Gong, Y., & He, A. (2025). A review of time series prediction models based on deep learning. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3602791

[24] Yan, L., Peng, J., Gao, D., Wu, Y., Liu, Y., Li, H., ... & Huang, Z. (2022). A hybrid method with cascaded structure for early-stage remaining useful life prediction of lithium-ion battery. *Energy*, *243*, 123038. https://doi.org/10.1016/j.energy.2021.123038

[25] Nong, Y. (2025). AI-Driven Predictive Cascade Failure Analysis Using Multi-Modal Environmental-Infrastructure Data Fusion Real-Time Prediction Framework for Critical Energy

Infrastructure. *Authorea Preprints*. https://doi.org/10.36227/techrxiv.176288076.69687745/v2

[26] Gaugel, S., & Reichert, M. (2023). Industrial transfer learning for multivariate time series segmentation: a case study on hydraulic pump testing cycles. *Sensors*, *23*(7), 3636. https://doi.org/10.3390/s23073636

[27] Liu, F., Chen, L., Zheng, Y., & Feng, Y. (2022). A prediction method with data leakage suppression for time series. *Electronics*, *11*(22), 3701. https://doi.org/10.3390/electronics11223701

[28] Salehin, I., & Kang, D. K. (2023). A review on dropout regularization approaches for deep neural networks within the scholarly domain. *Electronics*, *12*(14), 3106. https://doi.org/10.3390/electronics12143106

[29] Wang, M., Chen, L., & Chen, H. (2022). Multi-strategy learning boosted colony predation algorithm for photovoltaic model parameter identification. *Sensors*, *22*(21), 8281. https://doi.org/10.3390/s22218281

[30] Wang, Y., Wu, H., Dong, J., Liu, Y., Wang, C., Long, M., & Wang, J. (2026). Deep time series models: A comprehensive survey and benchmark. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. https://doi.org/10.1109/TPAMI.2026.3690845

[31] Ren, L., Jia, Z., Laili, Y., & Huang, D. (2023). Deep learning for time-series prediction in IIoT: progress, challenges, and prospects. *IEEE transactions on neural networks and learning systems*, *35*(11), 15072-15091. https://doi.org/10.1109/TNNLS.2023.3291371

[32] Zhang, Q. (2026). Research on Multimodal Prediction Model of Sports Event Ticket Revenue Based on Transformer. *International Scientific Technical and Economic Research*, *4*(2), 124-147. https://doi.org/10.71451/ISTAER2618

[33] Zhou, H. (2026). Research on the Fusion Model of DeepFM and XGBoost for Digital Consumer Behavior Prediction. *International Scientific Technical and Economic Research*, *4*(2), 98-123. https://doi.org/10.71451/ISTAER2617

[34] Qin, Y. (2026). Research on Long Sequence Learning Behavior Modeling Based on Transformer-XL. *International Scientific Technical and Economic Research*, *4*(2), 1-20. https://doi.org/10.71451/ISTAER2613

[35] Hodson, T. O. (2022). Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not. *Geoscientific Model Development Discussions*, *2022*, 1-10. https://doi.org/10.5194/gmd-15-5481-2022

[36] Xu, H. (2026). A Deep Reinforcement Learning Signal Control Algorithm for Traffic Carbon Emission Optimization. *International Scientific Technical and Economic Research*, *4*(1), 200–221. https://doi.org/10.71451/ISTAER2610

[37] Chen, G. (2026). Research on algorithm improvement of ARIMA-LSTM hybrid model in time series prediction of inflation rate. *International Scientific Technical and Economic Research*, *4*(1), 90-122. https://doi.org/10.71451/ISTAER2605

[38] Ding, Y., & Chen, G. (2026). Joint Prediction Model of Reservoir Parameters Based on Multimodal Transformer Graph Neural Operator Physical Constraint Network. *International Scientific Technical and Economic Research*, *4*(1), 70-89. https://doi.org/10.71451/ISTAER2604

[39] Zeng, X. (2026). Cross-Border Trade Fraud Detection via Integrated Heterogeneous Graph Neural Network and XGBoost. *International Scientific Technical and Economic Research*, *4*(1),47-69. https://doi.org/10.71451/ISTAER2603

[40] Wang, W., Shen, S., & Wang, Y. (2026). Forecasting Short-Term Export Volumes with Hybrid

Models Integrating SARIMA with Attention-Based LSTM, *International Scientific Technical and Economic Research*, 4(1),1-22. https://doi.org/10.71451/ISTAER2601

APA Citation

Chen, G. (2026). Research on an Energy Economic Demand Time Series Prediction Model Based on the Integration of XGBoost and Deep Learning. *Journal of Discovery Core*, *1*(1), 1–18. **https://doi.org/10.67541/jdc2601**