

Short-Term Electricity Load Forecasting Based on WOA-LSTM model

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ABSTRACT

Electricity load forecasting is a critical component in ensuring the safe, stable, and economical operation of power systems. However, the nonlinear and dynamic characteristics of load data impose limitations on the accuracy and generalization capabilities of traditional forecasting methods. To address this, this paper proposes a hybrid model (WOA-LSTM) based on the Whale Optimization Algorithm (WOA) and Long Short-Term Memory (LSTM) networks to achieve high-precision forecasting of ultra-short-term electricity loads. This model leverages WOA's global search capability to adaptively optimize LSTM's key hyperparameters, thereby enhancing the model's convergence speed and predictive performance. The LSTM network effectively captures the temporal dependency features of load sequences through its memory gate mechanism, enabling precise modeling of complex nonlinear trends. Experiments validate the model using power load data (15-minute sampling interval) from the 2016 Electrical Engineering Mathematical Modeling Competition, with data divided into training and testing sets. The results demonstrate that the WOA-LSTM model outperforms the single LSTM and other comparison models in metrics such as Root Mean Square Error (RMSE) and Coefficient of Determination (R^2), achieving an improvement in prediction accuracy of approximately 10% to 12%. This model provides efficient and reliable decision support for power grid load scheduling and intelligent energy management, offering significant reference value for enhancing renewable energy utilization rates and achieving the dual carbon goals.

KEYWORDS

Electricity load forecasting; Whale optimization algorithm; LSTM model; Hybrid model; Intelligent optimization

1. INTRODUCTION

Electricity load forecasting serves as a crucial foundation for smart grid operation and optimized dispatch, with its prediction accuracy directly impacting the stability and economic efficiency of power systems [1]. Accurate load forecasts enable grid operators to rationally schedule generation plans and power dispatch, thereby reducing energy waste and enhancing the safety and sustainability of system operation [2].

However, traditional load forecasting models struggle to effectively capture the nonlinear and time-varying characteristics of power load sequences, resulting in limited predictive performance when confronted with real-world scenarios involving multi-factor coupling and high uncertainty [3]. Consequently, incorporating machine learning and deep learning methods with stronger nonlinear modeling capabilities has emerged as a current research focus.

Long Short-Term Memory (LSTM) networks are widely applied in power load forecasting due to their ability to capture long-term dependencies in time series data [4]. Compared to traditional neural

networks, LSTMs demonstrate significant advantages when handling load data characterized by non-stationarity, periodicity, and pronounced sudden changes [5]. However, the predictive performance of LSTM models heavily relies on hyperparameter tuning, such as learning rate and time step length. Manual trial-and-error or grid search methods for hyperparameter optimization often suffer from low efficiency and susceptibility to local optima, making it challenging to achieve optimal model configurations.

In recent years, researchers have begun integrating swarm intelligence optimization algorithms with deep learning models to enhance prediction accuracy and model robustness. As an emerging bio-inspired optimization algorithm, the whale optimization algorithm (WOA) has been widely applied in parameter optimization for machine learning models due to its strong global search capability, simple parameters, and fast convergence speed [6]. Given the outstanding performance of LSTM and WOA in power load forecasting tasks, this paper combines both to achieve high-precision forecasting of ultra-short-term power loads. Due to the brief time interval of ultra-short-term forecasting, the influence of meteorological factors is relatively minor [7], so this study excludes meteorological factors from consideration. Final experimental results demonstrate that the proposed hybrid model outperforms single models in forecasting accuracy, further enhancing the reliability of power load forecasting.

2. METHODOLOGY

2.1. Using WOA optimization algorithms for model parameter tuning

The Whale Optimization Algorithm (WOA) is an intelligent optimization algorithm inspired by the group hunting behavior of humpback whales, proposed by Mirjalili and Lewis (2016) [8]. This algorithm achieves global optimization by simulating whale hunting mechanisms in the ocean, including encircling prey, bubble net attacks, and spiral tracking. Its core concept lies in employing a group-based cooperative evolution strategy to dynamically balance global exploration and local exploitation, thereby enhancing the convergence speed and accuracy of optimization.

2.2. Using LSTM Components for Long-Term Dependency Capture

The emergence of recurrent neural networks (RNN) solves the problem that traditional neural networks have difficulty in effectively extracting features from large amounts of data when dealing with time series prediction. When dealing with long sequence programs, RNNs suffer from gradient vanishing or gradient mutation. As one of the variants of RNN structure, the birth of LSTM solves the inherent problems of RNN to some extent. LSTM was first proposed by Schmidhuber et al (1997). Compared to RNN, LSTM adds input gates (it), forgetting gates (ft), output gates (ot), and storage units (ct). The core of LSTM is the information about the state of the storage units, which can be added or deleted under the control of the three gates. The overall structure of the LSTM neural network is shown in Figure 1.

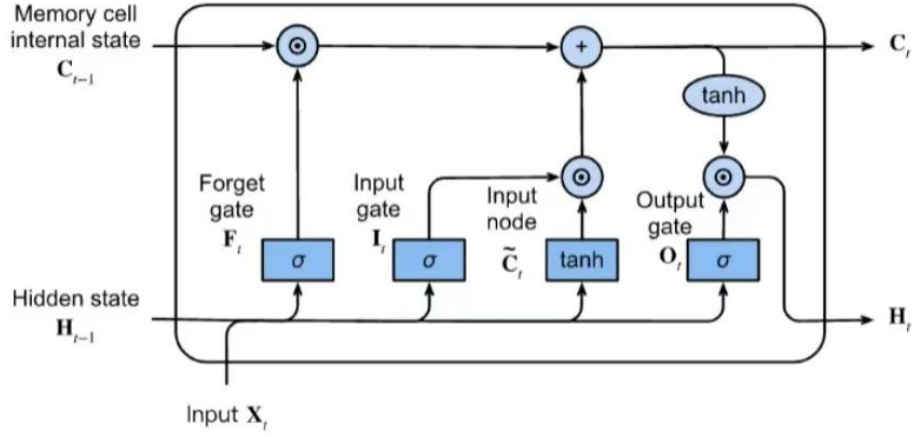


Figure 1. LSTM internal structure diagram

The mechanism of the LSTM unit is described as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

$$c_t = (f_t * c_{t-1} + i_t * \tilde{c}_t) \quad (5)$$

$$h_t = o_t * \tanh(c_t) \quad (6)$$

In the first step, the LSTM model determines the information needed to forget the current cell state. This process is realized through the forgetting gate, whose main function is shown in equation (1), where W_f and b_f are the weight matrix and bias of the oblivious gate, respectively, x_t is the current input to the storage cell, h_{t-1} is the output, and c_t is the cell state. Second, the LSTM model determines what information needs to be added to the cell state, a process that is realized by inputting the gate and the state information of the candidate cell, \tilde{c}_t , whose main function is as in Eqs. (2)(4). Immediately after obtaining \tilde{c}_t with it, the cell state needs to be updated. As shown in Equation (5), $f_t * c_{t-1}$ indicates that the forgetting gate selectively forgets some of the state information of the old cell; $i_t * \tilde{c}_t$ indicates that the input gate adds some new information to the cell state. Finally, after updating the new cell state, the output depends not only on the new cell state but also on the output gate, as shown in Eqs. (3)(6).

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1. Data Source

The experiment utilized power load data from January 1, 2009, to January 10, 2015, provided by the 2016 Electrical Engineering Mathematical Modeling Competition [9], with a sampling interval of 15 minutes. Data from January 1, 2009, to January 8, 2015, served as the model input, divided into training and testing sets at a ratio of 0.8. Additionally, these experiments were conducted in a Python 3.11 environment running on a Windows 11 operating system, equipped with a 64-bit AMD64 processor.

3.2. Performance Metrics

Four commonly used error detection methods, namely MAE, RMSE, NMSE, and R2, are used in this study to compare the accuracy of experimental models. This study also uses these metrics as a basis for evaluating the predictive effectiveness of multiple prediction models. The formulas for the above four performance criteria are as follows:

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (8)$$

$$NMSE = \frac{\sum_{t=1}^n (y_t - \hat{y}_t)}{\sum_{t=1}^n (y_t - \bar{y}_t)^2} \quad (9)$$

$$R^2 = 1 - \frac{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2}{\frac{1}{n} \sum_{t=1}^n (y_t - \bar{y}_t)^2} \quad (10)$$

Where y_t is the actual power load data, \hat{y}_t is the predicted power load data, and n is the number of power load data.

3.3. Analysis of Results

Electricity load data exhibits nonlinear characteristics. Model comparisons reveal that single models such as LSTM and GRU perform poorly when handling nonlinear problems. Therefore, this study proposes utilizing an intelligent optimization algorithm—the WOA model—to optimize model parameters and enhance prediction accuracy. Table 1 lists the numerical results of the performance metrics for the aforementioned prediction models. Figure 2 presents the RMSE and MAE values for each model. Based on these results, the WOA-LSTM model demonstrates the best performance. Its RMSE value is 415.5528, lower than that of other models. Regarding model fitting quality (R^2), the WOA-LSTM model achieves the highest prediction accuracy with a model fitting value of 0.9624. In summary, the WOA-LSTM model outperforms other models and achieves superior prediction results.

Table 1. Prediction performance for each model

Models	RMSE	MAE	R2	NMSE
LSTM	479.4250	292.9836	0.9500	0.0500
GRU	490.1221	315.2125	0.9452	0.0548
WOA-LSTM	415.5528	250.7489	0.9624	0.0376

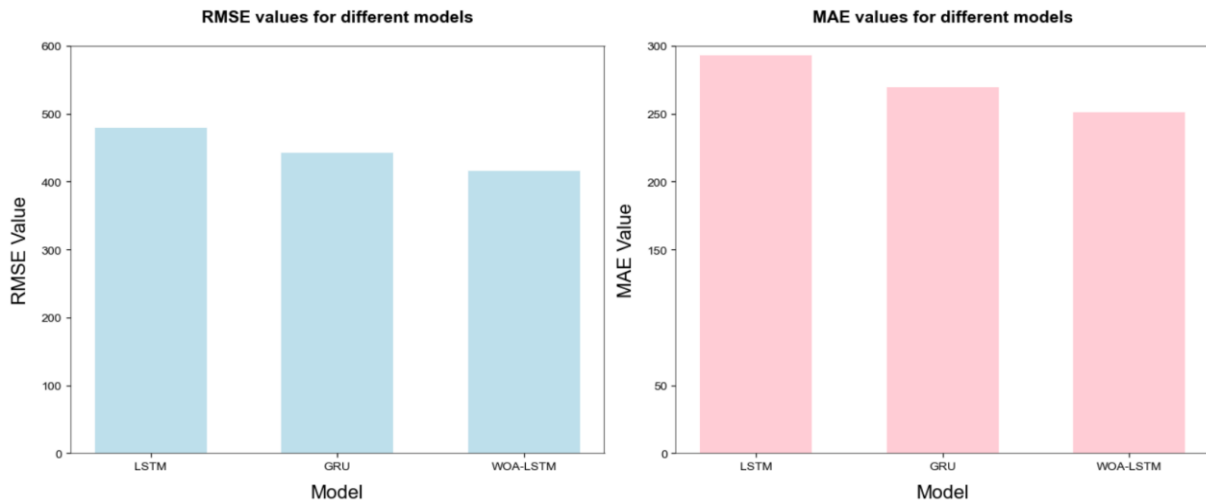


Figure 2. Comparison of RMSE and MAE values for different models

4. CONCLUSION

Electricity load data exhibits distinct characteristics such as nonlinearity, randomness, and dynamic fluctuations, posing significant challenges for load forecasting. To further enhance the prediction accuracy and stability of the model, this paper constructs a hybrid forecasting model combining the Whale Optimization Algorithm (WOA) with a Long Short-Term Memory (LSTM) network based on electricity load data provided by the 2016 Electrical Engineering Cup Mathematical Modeling Competition. The WOA algorithm employs a global optimization mechanism to adaptively tune the critical hyperparameters of the LSTM model, effectively avoiding the blindness of manual parameter selection and the issue of local optima. This significantly enhances the model's predictive performance. Experimental results demonstrate that the WOA-LSTM model outperforms the standalone LSTM model and other comparison models in terms of prediction accuracy, convergence speed, and generalization capability. This validates the model's effectiveness and robustness in handling complex nonlinear load data.

Future research may further integrate multi-source heterogeneous data from meteorology, economics, and other domains to expand the application potential of the WOA-LSTM model in scenarios involving multiple input variables. Concurrently, advanced intelligent optimization algorithms (such as adaptive parameter WOA) can be incorporated into the model optimization process to enhance its self-learning capabilities and generalization performance. Leveraging cloud computing and big data technologies, the WOA-LSTM model holds promise to play an increasingly vital role in load forecasting for smart grids and energy dispatch decision-making.

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