Short-term load forecasting with bidirectional LSTM-attention based on the sparrow search optimisation algorithm

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Abstract: Aiming at the complexity and diversity of short-term power load data, a bidirectional long short-term memory (BILSTM) prediction model based on attention was proposed for the pretreatment collected data, and the different kinds of data were divided to obtain a training set and test set. The BILSTM layer was used for modelling to enable the extraction of the internal dynamic change rules of features and reduce the loss of historical information. An attention mechanism was used to give different weights to the implied BILSTM states, which enhanced the influence of important information. The sparrow search (SS) algorithm was used to optimise the hyperparameter selection process of the model. The test results showed that the performance of the proposed method was better than that of the traditional prediction model, and the root mean square errors (RMSEs) decreased by (1.18, 1.09, 0.60, 0.54) and (2.11, 0.45, 0.21, 0.11) on different datasets.

Keywords: short-term load prediction; sparrow search algorithm; neural network; weight assignment; attention mechanism.

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1 Introduction

Load forecasting involves analysing historical load data with specific methods or models to estimate power system demand based on system fluctuations and changes in external factors (e.g., meteorological factors at load locations) (Yan et al., 2020). Load forecasting data form the basis for power system dispatch, and improving the accuracy of these data is essential to power system development (Liu et al., 2020).

The available short-term load forecasting methods can be divided into three main categories (Li, 2021). The first contains traditional statistical methods, mainly including linear regression (LR) (Wang, 2018), autoregression (AR) (Xu et al., 2019), the autoregressive moving average (ARMA) (Liu and Gao, 2020), and so on. These methods are simple in structure and easy to build, but the distributional characteristics of the input data exert a significant influence on the model outputs. The second category contains machine learning methods, including grey systems, support vector machines (SVMs) (Johnson and Shanmugam, 2011), and artificial neural networks (ANNs) (Naik et al., 2021). SVM algorithms can be applied for linear or nonlinear problems with low generalisation error rates. Furthermore, they are capable of solving high-dimensional problems in traditional algorithms. However, SVM algorithms are difficult to implement with large-scale training samples, and these algorithms are also sensitive to missing data. The backpropagation (BP) neural network in an ANN is a learning algorithm for multilayer forwarding (Lu et al., 2020) that can continuously modify the connection weights between the artificial neurons that make up the forward multilayer network. In this way, the forward multilayer network can transform the input information into the desired output information. However, the convergence rate of this method is slow, and the number of hidden nodes in the network is difficult to determine. The third category contains combined model prediction methods, which combine optimisation algorithms to optimise the multiple hyperparameters present in the given model to achieve improved prediction accuracy. At present, the most widely used optimisation algorithms are the SS algorithm, particle swarm optimisation (PSO) algorithm, whale optimisation algorithm (WOA), and genetic optimisation algorithm (GA). The SS algorithm has good global exploration and local development abilities, as it takes all factors into account and makes the sparrows in the population move to the global optimal value; it can quickly converge to the optimal value.

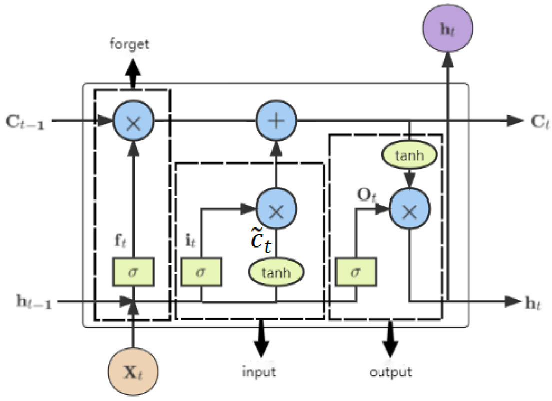
Power load data can now be automatically acquired. Analysing the data acquisition and power consumption abilities of distribution transformers to end-users achieves the purpose of electricity monitoring and metre reading, and the system automatically transmits these data to a data acquisition system. However, electromagnetic wave noise interference in the collected data can affect data quality and reduce prediction accuracy. In this paper, first, the data preprocessing method is used to eliminate data noise. Second, a two-way long short-term memory (LSTM) layer is used to learn the positive and negative internal feature laws of power load data and extract hidden matrix features to generate weight values in combination with an attention mechanism. At the same time, the SS algorithm is used to optimise the selected model hyperparameters, and finally, prediction results are output. Experimental comparisons are performed with the BP algorithm, LSTM time series algorithm, LSTM algorithm based on S optimisation, bidirectional LSTM (BILSTM) algorithm based on attention mechanism, and BILSTM algorithm based on an attention mechanism optimised by the SS algorithm. Regarding short-term power load forecasting, the average percentage error and long short-term memory RMSE of the forecasting results yielded by the attention-based BILSTM model optimised with the S algorithm are less than those of other prediction models.

2 Methods

2.1 BILSTM

BILSTM is a combination of forward and backward LSTM. In the forward process, an LSTM model is input; in the backward process, the LSTM model is input in the reverse direction. LSTM is a particular cyclic neural network that controls the transmission state through its gated state, remembers the information that it must save for a long time period, and forgets the unimportant information. Its structure is shown in Figure 1.

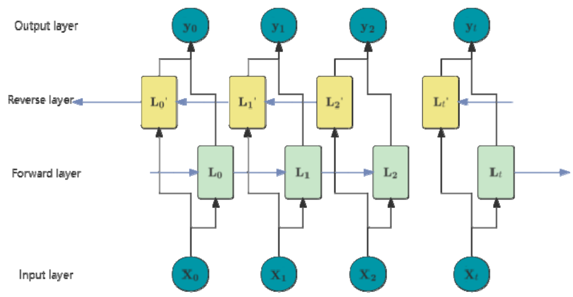
Figure 1 Schematic diagram of the LSTM network structure (see online version for colours)



The LSTM unit has forget, input, and output gates. In Figure 1, C_{t-1} represents the state of the previous cell; h_{t-1} represents the output of the previous unit; and X_t represents the current input. f_t is the degree of information forgetting; it represents the degree of input information retention; and indicates the newly entered information. tanh is the activation function and represents the hyperbolic tangent function; O_t indicates the output information.

The network structure of BILSTM has four parts: an input layer, a forward layer, a reverse layer, and an output layer. This model allows the relationships of load sequences to be extracted from the forward and backward directions and connected to the same output so that bidirectional temporal features can be extracted from the input power load sequence data by using BILSTM. The network structure of BILSTM is shown in Figure 2 (He et al., 2018).

Figure 2 Schematic diagram of the BILSTM network structure (see online version for colours)



2.2 Attention mechanism

An attention mechanism is a resource allocation mechanism that mimics the attention of the human brain. In general, the human brain focuses its attention on the areas of interest at a particular moment, reducing or even eliminating the attention paid to other areas to obtain more detailed information that needs to be focused on, thereby suppressing other useless information, ignoring irrelevant information and amplifying the required information (Li et al., 2019). An attention mechanism can help improve a model's accuracy by assigning sufficient attention to critical data and highlighting the impact of focused information.

2.3 SS algorithm

The SS algorithm is a new type of swarm intelligence optimisation algorithm proposed by Xue and Shen (2020). Originating from the behaviour of sparrows during foraging, the algorithm has the advantages of strong merit-seeking ability and fast convergence. The specific rules are as follows.

1 Bird member discoverers (producers) and joiners or followers (scroungers) in the SS model are defined.

2 Population initialisation is performed through the following matrix:

$$X = \begin{bmatrix} X_1^1 & X_1^2 & \cdots & X_1^d \\ X_2^1 & X_2^2 & \cdots & X_2^d \\ \cdots & \cdots & \ddots & \cdots \\ X_n^1 & X_n^2 & \cdots & X_n^d \end{bmatrix} \tag{1}$$

where X^d denotes the dimension to be optimised and X_n represents the number of sparrow populations.

3 The discoverer, which is generally randomly selected from 10%–20% of the population, usually has a high energy reserve and is responsible for searching for areas with abundant food throughout the population; it behaves as a leader in the terms of the directions and ranges of the other joiners. The high energy reserves are determined by the individual sparrow adaptability values.

The adaptability values of sparrows are expressed as follows:

$$Fx = \begin{bmatrix} \mathrm{f}\left(\left[x_1^1 \; x_1^2 \; \cdots \; x_1^d\right]\right) \\ \mathrm{f}\left(\left[x_2^1 \; x_2^2 \; \cdots \; x_2^d\right]\right) \\ \cdots \\ \mathrm{f}\left(\left[x_n^1 \; x_n^2 \; \cdots \; x_n^d\right]\right) \end{bmatrix} \tag{2}$$

where X^d denotes the dimension to be optimised, X_n represents the number of sparrow populations, and f([x]) represents the fitness value.

During each iteration, the position of the discoverer is updated as follows (Zhao and Wang, 2020; Chen et al., 2021):

$$x_{ij}^{t+1} = \begin{cases} x_{ij}^t \cdot \exp\left(-\dfrac{i}{\alpha \cdot t_{\max}}\right), & R_2 < ST \\ x_{ij}^t + QL & R_2 \geq ST \end{cases} \tag{3}$$

where t denotes the current number of iterations; j denotes the current dimension with J = 1, 2, 3, …, d; x_{ij}^{t+1} denotes information about the position of the first sparrow in the $j^{\{th\}}$ dimension during the $t^{\{th\}}$ iteration; α is a random number that lies in (0, 1); Q is a random number subject to a normal distribution; L is an all-1 unit matrix of size 1×d; R_2($R_2 \in$ [0, 1]) indicates an early warning value; and ST($ST \in$ [0, 5, 1]) indicates the safety threshold. When the warning value R_2< the safety threshold ST, no predators are present, and the finder enters the food search mode. When the warning value $R_2 \geq$ the safety threshold ST, the race is threatened by the present predator, the sparrow needs to go elsewhere to forage, and a new fitness value needs to be calculated.

4 The joiners also monitor the finder's energy level status to determine whether the finder has found better food while obtaining food in the area found by the finder, and the joiners actively compete for food resources when the finder's energy level is high. The accessed locations are updated as follows:

$$X_{ij}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{X_{worst}^t - X_{ij}^t}{i^2}\right) & i > \dfrac{2}{n} \\ X_p^{t+1} + \left|X_{ij}^t - X_P^{t+1}\right| \cdot A^* \cdot L & i \leq \dfrac{2}{n} \end{cases}, \tag{4}$$

where X_{worst}^t denotes the current global worst position; X_p^{t+1} denotes the discoverer's optimal position after iteration t + 1, i.e., the location with the best food; A denotes a matrix of size 1×d with each element randomly assigned –1 or 1, where this matrix satisfies $A^* = A^T(AA T)^{-1}$; and n denotes the total number of sparrows.

$i > \dfrac{2}{n}$ means that the sparrows are very hungry (because they are poorly adapted), and they need to look elsewhere for food; $i > \dfrac{2}{n}$ means that the sparrows are near the best food found by the finder, and it is likely that competition for food resources will turn the sparrows themselves into finders.

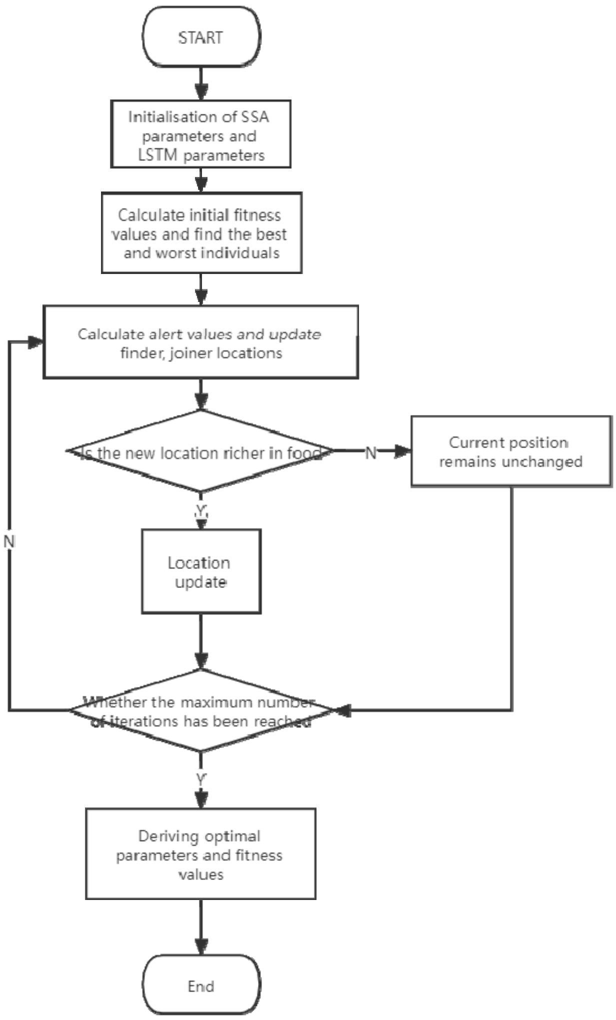
5 When a sparrow is fully aware of dangers nearby (which does not necessarily mean that a predator is present), it actively approaches a safe area, i.e., a circle or its surrounding partners.

$$X_{ij}^{t+1} = \begin{cases} X_{best}^t + \beta\left|X_{ij}^t - X_{best}^t\right| & f_i > f_g \\ X_{ij}^t + K \cdot \dfrac{\left|X_{ij}^t - X_{worst}^t\right|}{(f_i - f_w) + \omega}, & f_i \leq f_g \end{cases} \tag{5}$$

where X_{best}^t denotes the global optimal position after t iterations; β denotes the iteration step control parameter, which is a random number that follows a standard normal distribution; $K \in$ [–1, 1] denotes a random number from –1 to 1 representing the fitness value of the current individual sparrow; fi denotes the global optimal fitness value; f_g denotes the global worst fitness value; and ω is a constant to avoid zero in the denominator.

When $f_i > f_g$, the given sparrow is at the boundary of the group's range and is vulnerable to predators; when $f_i > f_g$, the sparrow is in the middle of the group, is aware of the danger, and needs to move closer to other sparrows at random.

Figure 3 SS-optimised LSTM flow



3 Proposed combined models

3.1 SS-optimised LSTM model

According to the description of the LSTM model in Section 2.2, it is clear that the parameters choices in short-term electricity load forecasting directly affect the accuracy of the constructed model (Dong et al., 2022). Therefore, in this paper, the SS algorithm referenced in Section 2.3 is applied to optimise the learning rate, the number of training iterations, and the numbers of two types of LSTM nodes. Figure 2 shows the optimisation process, and the specific steps are as follows:

Step 1 Initialise the population, the number of iterations and the ratios of predator to joiners.

Step 2 Calculate the fitness values and rank them.

Step 3 Update the predator positions through equation (3).

Step 4 Update the joiner positions through equation (4).

Step 5 Update the position of the alert value through equation (5).

Step 6 Calculate the fitness values and update the sparrow positions.

Step 7 Judge whether the stopping condition is satisfied; if so, exit with the output result; otherwise, repeat Steps 2–6.

3.2 SS-optimised BILSTM-attention model

The essence of SS optimisation is the foundation of a maximum or minimum fitness function value. In this paper, the fitness function minimises the mean squared difference between the desired output and the actual output of the BILSTM-Attention network, i.e., it finds the set of network hyperparameters that minimises the error of BILSTM-Attention. The whole optimisation process is shown in Figure 4. The SS-optimised BILSTM-Attention model is composed of a BILSTM-Attention part and an SS part. In the BILSTM-Attention part, first, the incoming parameters are decoded according to the principle of the above SS algorithm to obtain the number of iterations, the learning rate, and the number of nodes in each hidden layer. Then, the network training process proceeds on the divided training set. Finally, the prediction procedure is carried out on the test set to obtain the mean squared error between the actual output value and the desired output value, and the mean squared error is returned to the SS part as the fitness value. The SS part executes the movements of predators, joiners, and vigilantes on the basis of their fitness values to update the population and the global value to optimal states. An optimised network hyperparameter is finally obtained through this method.

The solution process is as follows:

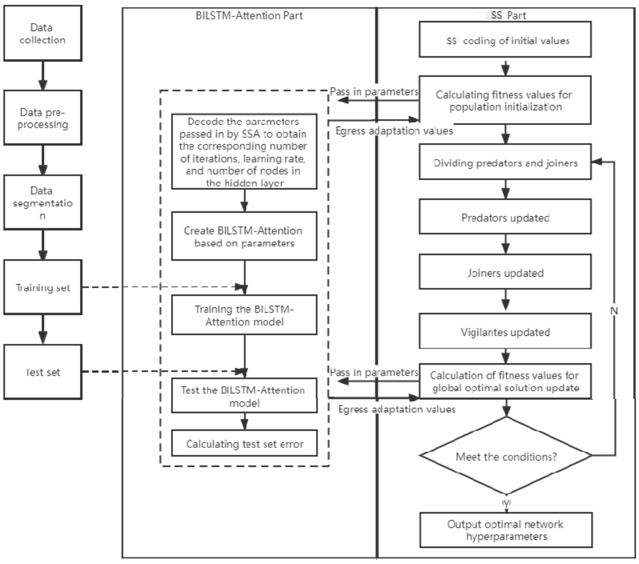
Step 1 Merge the preprocessed historical load with the daily feature data and divide the data into a training set and test set.

Step 2 Build a model based on the BILSTM-Attention mechanism and input the 24-hour load, average temperature, maximum temperature, minimum temperature, relative humidity, and weekday type values before the forecast date into the model as the 29 feature values of the previous day. Similarly, the average temperature, maximum temperature, minimum temperature, relative humidity, and weekday type of the forecast day are set as the five feature input values to predict the day's load.

Step 3 Use the SS process described in 3.1 to perform the optimisation search. Parameters are passed in for modelling and training.

Step 4 Calculate the test set error.

Figure 4 SS optimisation-based BILSTM-attention flowchart



4 Simulation

Two real load datasets are used to validate the model proposed in this paper: one contains local data collected from a region in Zhejiang Province from February 13, 2010, to May 20, 2010, with a collection time interval of 1 h, and the other includes actual electricity load data from a region in Shaanxi Province for the period from May 1, 2021, to August 30, 2021, with 96 time points collected each day and a collection time interval of 15 min.

4.1 Data standardisation

Due to the different units of the collected data characteristics, the electrical load data are first harmonised, and the electrical load data are measured in hourly units. The prediction input features also include the average temperature, maximum temperature, minimum temperature, relative humidity, and weekday type, and the degrees of different coefficients are derived for different times of the week based on electricity usage. To improve the training effect of the model, a linearised mapping of week types is used to impute the values between [0, 1] and is calculated as follows (Qing-Song, 2020):

$$X^* = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{6}$$

where X^* denotes the normalised data, x represents the original data, X_{min} is the minimum value of the sample data and X_{max} is the maximum value of the sample data.

To assess the accuracy of the model, the mean absolute percentage error (MAPE) (Htike, 2018), RMSE (Gu, 2017), and determination coefficient (R2) (Li, 2021) are selected as the criteria for prediction accuracy in this paper, and their equations are calculated as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \times 100\% \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2} \tag{8}$$

$$R2 = 1 - \frac{\sum_{i=1}^{n}\left(x_i - y_i\right)^2}{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} \tag{9}$$

where x_i represents the actual value of the $i^{\{th\}}$ sample, y_i represents the predicted value of the $i^{\{th\}}$ sample, $\widehat{y_i}$ represents the actual value of the $i^{\{th\}}$ sample, $\overline{x}$ represents the actual mean value of the sample, and n represents the number of samples.

To demonstrate the validity of the model given in this paper, the results of BP, LSTM, SS-LSTM, and BILSTM-Attention models are compared with the results of the method proposed in the paper.

5 Results and discussion

5.1 Zhejiang Province forecasting results

The dataset used in this paper is the standard dataset for a certain location in Zhejiang. The data from 13 February 2010 to 19 May 2010 are used as the training set to predict the data for 20 May 2010, and the data for 20 May 2010 are used as the validation set for verification purposes. SS parameter optimisation is carried out for the fitness calculation; the mean squared error of the validation process is set as the fitness function to find a set of hyperparameters that minimise the error of the network.

The learning rate, number of training iterations, and number of nodes in the hidden layer of BILSTM-Attention are optimised by using SS. The adaptation convergence curve, the learning rate optimisation curve, and the training iteration optimisation curve are illustrated in Figures 5–7. Figures 8 and 9 show the optimisation curve for the number of LSTM hidden layer nodes.

Figure 5 Adaptation convergence curve (see online version for colours)

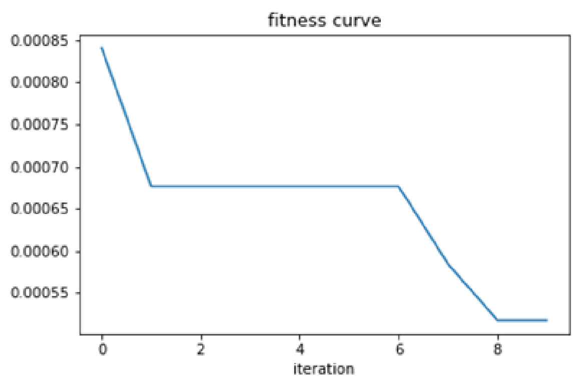


Figure 6 Learning rate optimisation curve (see online version for colours)

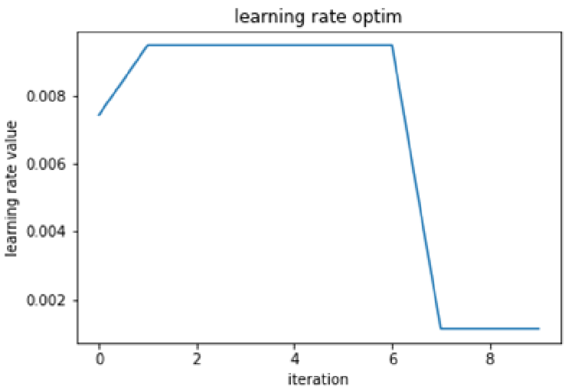


Figure 7 Number of training sessions for the optimisation curve

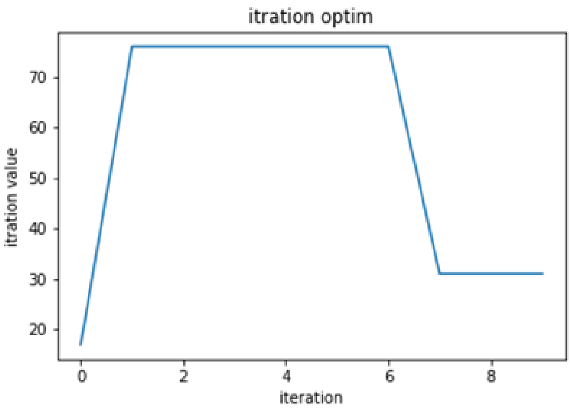


Figure 8 Node-seeking curve of the first implicit layer (see online version for colours)

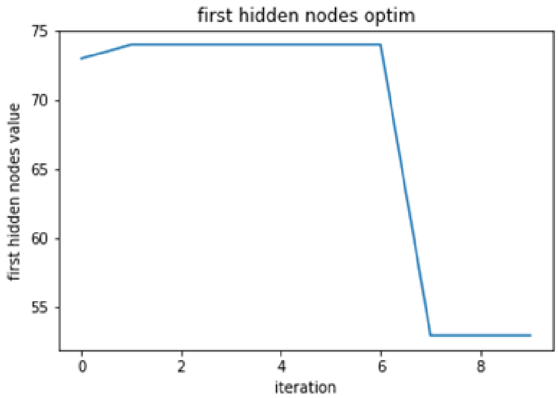


Table 1 Comparison among the prediction accuracies of different models

Models	*MAPE*	*RMSE*	R^2
BP	3.069%	2.467	96.47%
LSTM	2.818%	2.384	96.70%
SS-LSTM	2.092%	1.892	97.92%
BILSTM-attention	2.066%	1.827	98.06%
SS-BILSTM-attention	1.203%	1.291	99.03%

Figure 9 Node-seeking curve of the second implicit layer (see online version for colours)

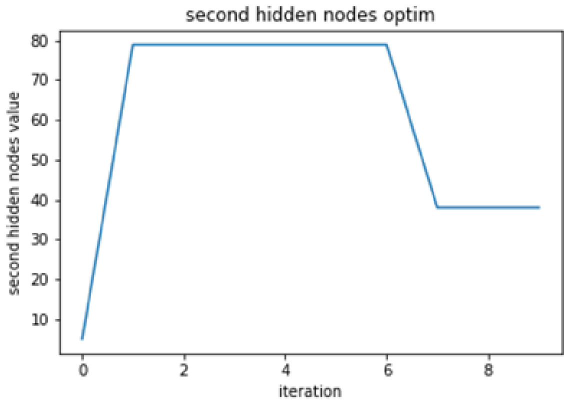
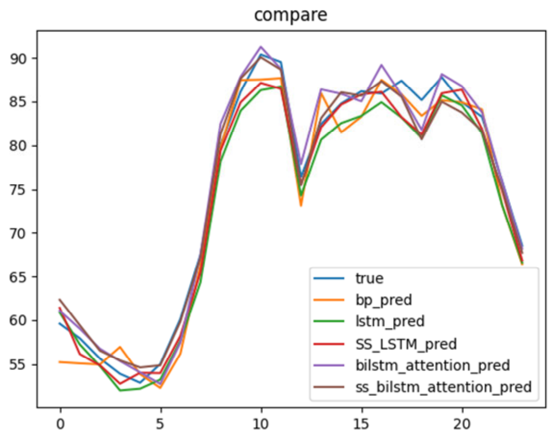


Figure 10 Predicted versus true values for each algorithm (see online version for colours)



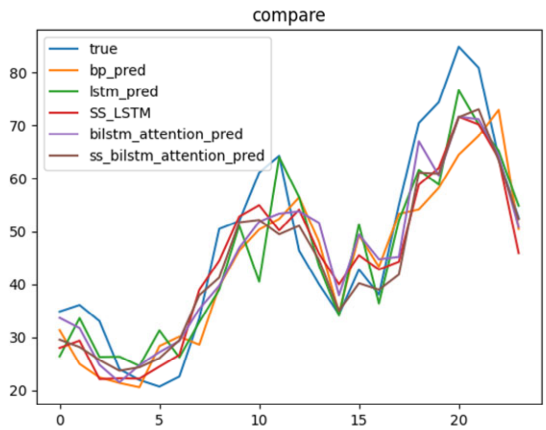
The evaluation metrics for the selected prediction day are listed in Table 1. It can be concluded that the proposed model reduces the MAPE by 1.87%, 1.62%, 0.89%, and 0.86% compared to those of the BP, LSTM, SS-LSTM, and BILSTM-Attention models, respectively, and the RMSE metrics are reduced by 1.18, 1.09, 0.60, and 0.54 compared to those of the traditional prediction methods. This indicates that the proposed model has better performance than these traditional prediction methods. The predicted results of the different models are shown against the true values in Figure 10.

5.2 *Shaanxi Province forecasting results*

The proposed method is applied to data collected from other provinces to verify its applicability. The electricity load data of a region in Shaanxi are divided into two parts. The data collected from May 1, 2021, to August 29, 2021, are used as the training set to predict the data for August 30, 2021, and the data on August 30, 2021, are used as the validation set for verification purposes.

Figure 11 compares the prediction accuracy of the proposed method with that of BP, LSTM, SS-LSTM, and BILSTM-Attention. It can be seen from Figure 11 that the prediction results of the model proposed in this paper are closest to the real values, and the proposed method has more accurate prediction results. It can better represent load variation patterns than other methods.

Figure 11 Predicted versus true values for each algorithm (see online version for colours)



Each evaluation index, as shown in Table 2, further verifies the rationality of the model developed in this paper. According to Table 2, the prediction accuracy of this model is the highest. Compared with those of the BP, LSTM, SS-LSTM, and BILSTM-Attention models, the MAPE of the proposed model is reduced by 4.58%, 0.57%, 1.13%, and 1.82%, respectively, and the RMSE indicators are reduced by 2.11, 0.45, 0.21 and 0.11, respectively.

Table 2 Prediction accuracy comparison

Models	*MAPE*	*RMSE*	R^2
BP	17.51%	9.633	72.72%
LSTM	13.50%	7.966	81.35%
SS-LSTM	14.06%	7.732	82.43%
BILSTM-attention	14.75%	7.632	82.88%
SS-BILSTM-attention	12.93%	7.521	83.37%

6 Conclusions and future work

To ensure the stability and reliability of a regional power supply, power load forecasting is an essential prerequisite. The accuracy of power load prediction results is significant for regional power network planning and construction. The prediction model proposed in this paper can excavate the internal laws of loads and other features in different regions. A BILSTM layer model containing an attention mechanism and the SS algorithm is used to achieve short-term load prediction. In the BILSTM-Attention model, bidirectional timing-based feature extraction improves the prediction accuracy yielded by the input information. Then, a weight vector is generated by the attention layer, and the vector matrix extracted by the hidden layer is multiplied. At the same time, the SS algorithm is used to iteratively optimise the network hyperparameters, and the parameters with the minimum errors are found and input into the model; then, the prediction results are output. Because load data have apparent positive and reverse regularity, in load prediction, not only historical loads but also the impact of future load on the prediction accuracy should be considered. The BILSTM model can perfectly meet the above requirements. The selection of the SS algorithm for solving the hyperparameters is determined based on the human history of versatility and uncertainty problems.

A comparison between the method proposed in this paper and the conventional methods reveals some uncontrollable factors exhibited by real datasets, leading to a lack of fit regarding the model training process and making the obtained graph description results unsatisfactory. Furthermore, in the future, more features will be added further to improve the accuracy of the developed short-term load prediction approach.

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