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Short-term Power Load Forecasting Based on WNR-LSTM — Take the Singapore Region as an Example

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Abstract: *In recent years, as the electrical energy of distributed storage has gradually increased, the randomness of load demand has increased. This makes it more difficult to rationally dispatch and store loads. How to quickly and accurately dig out more effective information and objective laws from the massive power load data, effectively clarify the instability and timing of load changes, and then reduce the consumption and accidents in dispatching is of great significance. This paper uses wavelet analysis and stochastic sparrow search algorithm to optimize LSTM neural networks to construct long- and short-term power load forecasting models, in Singapore as of December 2021 Empirical studies were conducted on the electricity load from 24 to January 23, 2022, as well as the corresponding peak-to-valley electricity prices, meteorological data and other related data. The results show that the long-term and short-term power load prediction model based on WNR-SSA-LSTM is compared with that of traditional LSTM In terms of neural networks, RMSE and MAPE were reduced by 4.000% and 1.7871%, model goodness-of-fit R2 increased by 0.0196, It is more suitable for short-term load forecasting.*

Keywords: *Short- and long-term power load, Wavelet noise reduction, LSTM neural network, Sparrow search algorithm*

1. Introduction

Therefore, in the environment of competition in the electricity market, accurate and accurate prediction of the power consumption in the future can help reduce the cost of power dispatch and loss [3]. In addition, since the momentary change of power demand requires that the system's power generation should be dynamically balanced with the change of load, improving the short-term prediction accuracy of the load is conducive to improving the utilization rate of equipment and improving the quality of power. Current predictions of electricity load are mainly divided into two categories: one using Kalman filtering[7], Fourier unfolding method[9], and autoregressive integral moving average model (ARIMA Time series forecasting models such as grey forecasting models[10] predict future load values based on the strong time characteristics and repeatability of electrical energy. However, due to the limited nonlinear approximation ability [3], it is difficult to break through the prediction accuracy. Another class of particle swarm optimization with nonlinear approximation and strong fault tolerance[10], generalized regression neural networks[9] and intelligent algorithms such as integrated algorithms [6] and support vector machines [8]. The development trend of power load consumption is suitable, and due to the time characteristics and suddenness of the data itself, machine learning methods are gradually widely used in the field of load prediction.

In this paper, a deep learning network based on wavelet analysis (WNR)[5] and sparrow search algorithm (SSA)[1] variants of LSTM is proposed the algorithm constructs a short-term power load prediction model. First, the original data is preprocessed with wavelet noise reduction, and then a variety of feature vectors are used as inputs in the form of time series to construct LSTM combined with sparrow search algorithm combined hybrid neural network, taking short-term power load in Singapore as an example for empirical research, in order to better solve the accuracy problem of short-term power load forecasting.

2. Short-term power load forecasting model

2.1. Filtering of impact load indicators

The literature [4] points out that the prior ability of neural network models to input data is weak, and screening and processing data indicators can help accelerate the convergence speed of neural networks and improve the actual effect of the model. Therefore, this paper uses the prior knowledge of applied load prediction (in natural language processing and posture and gesture perception) to divide the load input parameters into: recent load or similar daily load, weather information, date type. Therefore, the power load function can be expressed as:

$$L(t) = L_m(t) + L_e(t) + L_f(t) + L_r(t) \tag{1}$$

Where: $L(t)$ is the actual load detected at t-time; $L_m(t)$ is the regular initial load data at t-time; $L_e(t)$ load fluctuations due to weather factors at t-time; $L_f(t)$ is the load fluctuation caused by special events at t time, such as holidays, epidemics, etc.; $L_r(t)$ is the load fluctuation at t time due to random electricity consumption, etc. $L_r(t)$ as a load forecast Noise is processed during structural model building. Thus, known by equation (1), it is possible to increase $L_m(t)$, $L_e(t)$, and $L_f(t)$ Accuracy of forecasts to improve the accuracy of overall forecasts.

For $L_m(t)$, due to the stability of population change and the weakness of geographical change, the load of the same time under the same date one year ago is used as a parameter to obtain [3]; for $L_e(t)$. Because weather factors have a greater impact on short-term loads, especially humidity, wind, weather conditions, etc., hot and extremely cold will lead to great changes in the charge. Therefore, the weather forecast multi-factor data is used to determine the weather impact load $L_e(t)$; for $L_f(t)$, the Singapore working day is Monday to Friday, and the non-working day electricity consumption has decreased significantly. Therefore, this article uses the date type as one of the factors that affect the load forecast results. Quantify holidays to 2 and weekdays to 1 as input data inputs to the neural network.

Table 1: Summary of influencing factors

Influencing factors	features	Representation	Characteristic description	unit
Power data	$L(n,t)$	$X_1(n,t)$	Nth day t time data	MW
Historical power load data	$D(n,t)$	$X_2(n,t)$	n-day t-hour data of the previous year	MW
Date factor	$T(n,t)$	$X_3(n,t)$	Weekdays/holidays	0/1
Meteorological factors	$R(n,t)$	$X_4(n,t)$	t hour of temperature	℃
	$W(n,t)$	$X_5(n,t)$	t the time of rain or not	1
	$L(n,t)$	$X_6(n,t)$	t Moments of wind power	level

2.2. WNR-SSA-LSTM structural model construction

In a traditional RNN network, the structure of repeated neurons has only a simple part like a *tanh* layer. LSTM is also such a structure, the duplicate module has a special way to interact with the previous layer of the network different from a single neural network layer, but it is clear that the network built by this structure carries unstable time characteristics and has a non-linear fit ability is not strong, so this paper proposes an LSTM-based variant neural network The deep learning network combined with the sparrow search algorithm deliberately designs the structure and constituent elements to solve the defects in the standard RNN and traditional LSTM neural networks, Figure 1 is the LSTM Basic neurons.

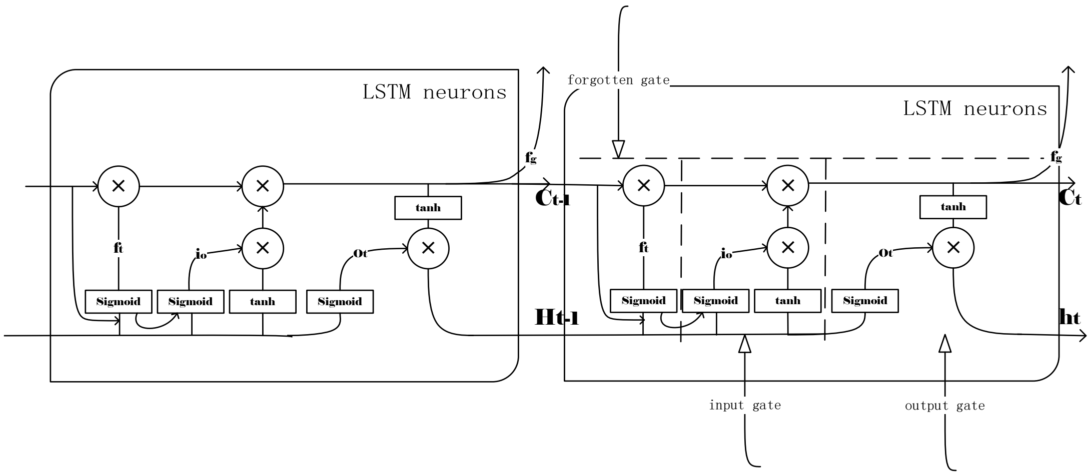

Figure 1: The basic unit of an LSTM network

The basic elements of the LSTM variant network consist of a forgotten gate, an input gate, and an output gate. The forgetting gate updates the forgetting parameter of the neuron to C_{t-1}, the memory parameter obtained from the previous level, and receives the intermediate output h_{t-1}. The data of the input gate are changed by the sigmoid and tanh functions, respectively, and the retention vector of the memory unit is determined. The calculation formula is shown in equations (2)-(5).

$$f_t = Sigmoid\left(W_f \cdot [C_{t-1}, h_{t-1}, x_t] + b_f\right) \tag{2}$$

$$i_t = Sigmoid(W_i \cdot [C_{t-1}, h_{t-1}, x_t] + b_i) \tag{3}$$

$$o_t = Sigmoid(W_o \cdot [C_t, h_{t-1}, x_t] + b_o) \tag{4}$$

$$f_g = O_t \cdot \tanh(C_t) \tag{5}$$

In order to improve the prediction accuracy of long-term and short-term loads, it carries a forget gate, which makes low-impact fluctuations discarded; the input gate is used to update the neuron state and determine the importance of the input information; the output gate is used to hide the state of the neuron and hide the state. passed to the next neuron to achieve the effect of memory. Compared with the traditional LSTM neural network, the use of the sparrow algorithm [1] enables the variant network to extract the latent features of the data in a large amount of load data, providing more time-continuous features and repeatability. The search and hunting ability of the sparrow search algorithm can greatly reduce the forgetting time and improve the convergence speed and training accuracy of the neural network. The WNR-SGD-LSTM network training model flowchart is shown in Figure 2.

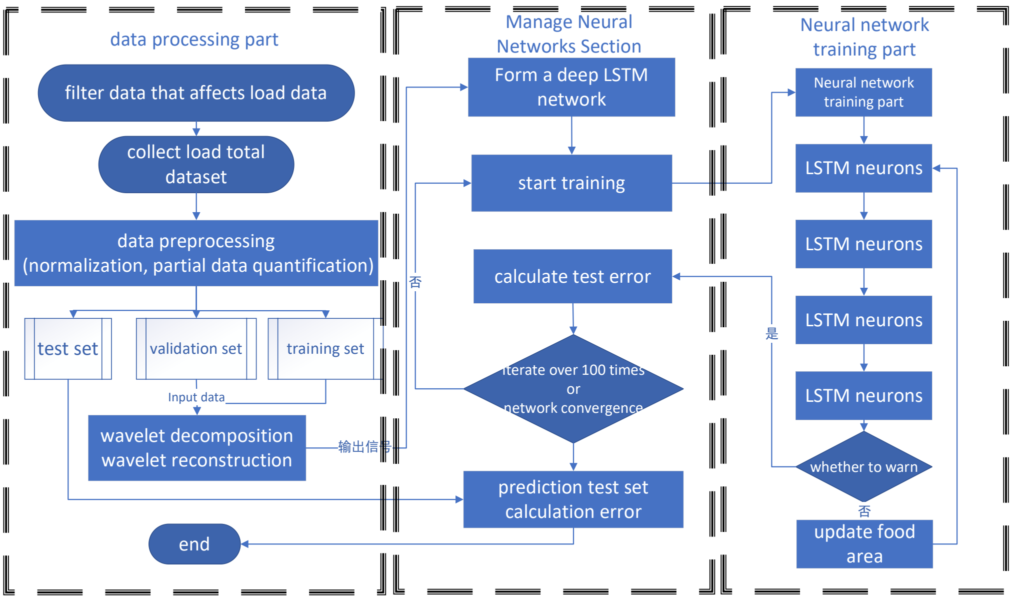

Figure 2: WNR-SGD-LSTM network model process structure model

2.3. Experimental evaluation indicators

To estimate the predicted performance, with reference to the load forecast indicator, calculate and compare the mean absolute percentage error y_{MAPE}, root mean squared error y_{RMSE}, and goodness-of-fit R^2.

$$y_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_{act(i)} - X_{pred(i)}}{X_{act(i)}}\right| \tag{6}$$

$$y_{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{act(i)} - X_{pred(i)}\right)^2}{n}} \tag{7}$$

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$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - f_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{8}$$

3. Case studies

3.1. Data Sources and Analysis

To verify the scientificity and reliability of the method proposed in this paper, this paper conducts experiments in Singapore from 24 December 2021 to 23 January 2022 1488 sets of data with December 24, 2020 to January 23, 2021 the 1488 sets of data of the day are used as the dataset, and the selected characteristics are shown in Table 1. Considering the relevance of the screened part to the original data, the gray correlation method was used for detection, and the results are shown in Table 2.

Table 2: Grey correlation of reference datasets

Reference datasets	Gray relevance
$X_1(n,t)$	0.9213
$X_2(n,t)$	0.7914
$X_3(n,t)$	0.8425
$X_4(n,t)$	0.7832
$X_5(n,t)$	0.7442

Obviously, since the gray correlation degree of the selected reference set is higher than 0.74, it can be considered that the dataset has a close correlation with the data set under test and is used as input data for building a machine learning model.

3.2. Data Preprocessing

1) Data quantification and outlier handling

In this paper, the wavelet noise reduction (hard threshold denoising)[6] method is used to denoise the power load data of this section in Singapore and the power load data of the previous year respectively, so as to preserve the spike characteristics and their continuity.

2) Data standardization

Using the standardization of min-max, the original data is linearly transformed, such as Equation 9.

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{9}$$

In Equation 9: x^* is the normalized input amount, and x_{max} and x_{min} are the maximum and minimum values of the term in the sample.

3) Training set and test machine division

90% of the 1488 sets of data were used as training datasets and 10% were used as test datasets for training and testing.

3.3. Example Calculation

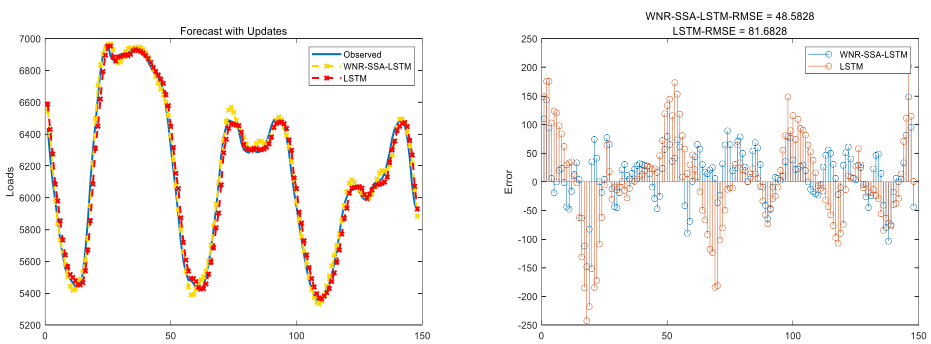

Figure 3: Prediction comparison chart and RMSE comparison chart

Through the study of the previous literature[3], this paper chooses to construct an LSTM neural network with four layers and an eigenvalue of 6. Among them, the SGD learning rate is 0.01, the momentum factor is 0.0, and the maximum number of iterations is 100 and through the iterative sparrow search algorithm to speed up convergence and improve prediction accuracy. The WNR-SSA-LSTM network undergoes 100 iterations and loses convergence at 40 generations and RMSE converges at 60 generations. After about 1 minute and 27 seconds, the neural network is trained to obtain the final prediction data and compare it with the traditional LSTM network The comparison curve of the prediction effect and the forecast indicator RMSE pair is shown in Figure 3.

The prediction results are predicted by the WNR-SSA-LSTMs network and the traditional LSTM network, and the predictors MAPE, RMSE and R are calculated according to the experimental evaluation indicators 2 indicators and training time T(s), the calculation results are shown in Table 3.

Table 3: Comparison of LSTM and WNR-SSA-LSTM

index	WNR-SSA-LSTM network	Traditional LSTM network
MAPE	0.06565	0.10565
RMSE	0.494178	0.812049
R^2	0.9900	0.9704
T(s)	87	121

From Table 3, it can be seen that the WNR-SSA-LSTM network predicts that the average absolute percentage error y_{MAPE} of the traditional LSTM network is 4% lower the root mean squared error y_{RMSE} is 31.7871% lower, and the model goodness-of-fit R^2 is increased by 0.0196, that is the prediction results based on the WNR-SSA-LSTM network are more accurate and effectively reduce the prediction error. The training time is shortened by 28% on the basis of the original network, and the rapid convergence brings less time cost to the prediction, so that the prediction result can bring more economic benefits.

4. Conclusion

Aiming at the long-term and short-term load prediction problem of power system, this paper proposes a neural network model based on WNR-SSA-LSTM hybrid algorithm. In the model, according to the prior knowledge processing, a valid reference data set is extracted, the effective reference data is subjected to wavelet noise reduction, and the data set after noise reduction is taken as input to the NR-SSA-LSTM neural network. The prediction results and comparison results show that the method can better fit the timing and complex nonlinear relationship of the load data, fully excavate more effective information from the massive data, give full play to the superiority of the sparrow search algorithm in accelerating the convergence speed and improving the training accuracy, accelerate the convergence speed of the neural network, and improve the prediction accuracy of the short-term load.

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