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Industrial and Commercial User Load Forecasting Model Considering Incentive Mechanism

Qiang YE [a], Yuqing CAI [a], Wuxiao CHEN [a,1], Zhijun JIANG [a], Jiaxin CAI [b], Kai LIU [c]

[a]*State Grid Fujian Marketing Service Center*
No. 9, Qinyuan Branch Road, Jin'an District
Fuzhou City, Fujian Province, 350011, China
[b]*State Grid Fujian Electric Power Co., Ltd*
No. 257, Wusi Road, Gulou District
Fuzhou City, Fujian Province, 350003, China
[c]*Technical Support Department*
Beijing SG-EPRI UHV Transmission Technology Company, Ltd
Beijing City, 100000, China

Abstract. In recent years, many industrial and commercial users have begun to participate in demand response, and demand response measures will affect future load demand, thus affecting the accuracy of load forecasting. Prediction problems for these particular users, this paper describes the implementation of an industrial user load forecasting model considering regulation and incentive by using the time series characteristics of historical data of power load and the influence of reward mechanism on the power demand behavior of industrial users. Firstly, the influence of production cost and reward mechanism on the power utilization behavior of industrial users is investigated. Then, the feature engineering, data preprocessing, improved Adam optimization algorithm, LSTM neural network algorithm, and model evaluation index of industrial user load forecasting are described. Finally, the effect of this method in actual industrial user load forecasting is demonstrated. The power load data of a printing and dyeing enterprise in East China is used for verification. Through the analysis of actual simulation verification, with a mean absolute percentage error (MAPE) of 3.12% on the training set and 5.22% on the test set, respectively, as shown by the experimental results, it has high prediction accuracy.

Keywords. load forecasting, long-short term memory, Adam algorithm, prediction model

1. Introduction

The stable operation of the power system is important for other infrastructure systems. At present, economic development is fast, the social demand for electricity is large, the scale of the power system is increasing, and the operating environment of the power grid is complex. Power system load forecasting is based on historical data and the future

[1]Corresponding author: Wuxiao CHEN, State Grid Fujian Marketing Service Center, No. 9, Qinyuan Branch Road, Jin'an District, Fuzhou City, Fujian Province, 350011, China; email: cwx91@qq.com

electricity demand forecast, which requires precision. Reasonable power planning requires accurate load forecasting.

High-precision load forecasting can encourage power operators to make more correct decisions to provide more reliable electricity protection [1]. High-power air conditioners, water heaters, and industrial production loads are important for power dispatching planning. At the same time, according to load forecasting results [2], the adjustable capacity of commercial and industrial loads can be obtained.

Due to the rapid development of new artificial intelligence technology, the data-driven artificial intelligence method has gradually become the main power system load forecasting scheme. In [3], experiments were carried out using different machine learning forecasting methods in the actual data of Panama, and the key factors affecting the electricity demand in the short term were analyzed. An integrated model training method with a weight updating mechanism is proposed based on BP, which improves the robustness of the model [4]. In [5], by comparing multiple machine learning and deep learning models, it is found that the CNN-LSTM hybrid model performs best. In [6], a prediction method based on the fusion of optimization algorithm, neural network, and modal decomposition is proposed and verified on three real data sets.

Unlike most existing work, we propose an industrial and commercial load forecasting model based on improved Adam-LSTM considering adjustment incentives. The model considers holiday, climate, and electricity price factors, and combined with the LSTM neural network, the power load of industrial and commercial users is predicted. Based on the Adam algorithm, the learning rate attenuation strategy is introduced to accelerate the update speed of the parameters, thereby enhancing the Adam algorithm's convergence rate at the initial stage and boosting the model's precision.

2. Analysis of Adjustment Incentive Effect

Because cement production needs plenty of energy in the cement industry, its energy consumption and production costs account for a relatively high proportion. Encouraged by the policy of time-of-use electricity price, cement plants may adjust their production plans and try to arrange the processes with higher power consumption to produce during the period of lower electricity price, thereby reducing production costs. This adjustment may impact load forecasting, especially during dramatic changes in electricity prices. Although the production process also requires a lot of energy and raw materials in the steel industry, its production process is fairly steady, and it is difficult to adjust the production plan quickly. Therefore, the time-of-use electricity price may have little effect on the load forecasting of the steel industry. In the textile industry, different processes have different energy needs.

For example, the dyeing and finishing process needs a lot of electricity, while the spinning process does not. Encouraged by the policy of time-of-use electricity price, textile enterprises may try to adjust the production plan and arrange the processes with higher power consumption to produce in the period of lower electricity price to reduce the production cost. This adjustment may have an impact on load forecasting. In the general equipment manufacturing industry, due to the relatively flexible production process, enterprises can adjust the production plan at any time according to the market demand so that the time-of-use electricity price may have a greater impact on load forecasting. At all events, enterprises may adjust production plans flexibly according to changes in electricity prices to minimize production costs.

3. Methodology

3.1. Setup of Input/output Variables

For the power load of industrial and commercial users, it is first essential to ascertain different environmental and time factors affecting the load, then through several simulation experiments to remove the superfluous environmental attributes with small influencing characteristics, to determine the temperature as input feature [7]. Moreover, commercial and industrial loads are somewhat constrained by working hours. The influence of working days and holidays should be considered, and day-type characteristics should be added as input characteristics. At the same time, the industrial and commercial loads have different production characteristics in different months, and the month characteristics are added as input characteristics. Therefore, we select the temperature, day type characteristics, load data, month and time-of-use electricity price characteristics of the 96 points before the predicted point as input feature X and output Y as load data of the predicted point.

3.2. Data Normalization

Linear function normalization scales the original data to the range of [0, 1] by a linear transformation. The equation is as follows:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X represents the initial data sequence, $X_{\min}$ indicates the minimum value in the X, and $X_{\max}$ indicates the maximum value in X.

3.3. Long-short-term Memory Network

LSTM neural network is an improved recurrent neural network [8], which can process the input according to time series, and overcomes the shortcomings of common RNN. It can deal with long-term dependence problems. That is, it can use information from the past to influence current and future outputs [9]. LSTM can perform better in longer sequences than ordinary RNNs.

Its basic unit is illustrated in Figure 1.

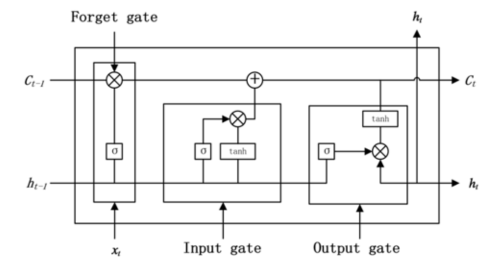

Figure 1. LSTM structure unit diagram

3.4. Adam Algorithm

Adam (Adaptive Moment Estimation) is an optimization algorithm of adaptive learning rates, a variation of a commonly used gradient descent method. Based on the RMSProp algorithm, Adam combines the momentum method and bias correction, overcomes some problems in the traditional gradient descent algorithm, and has good convergence and applicability.

The core idea of Adam is to adjust the learning rate of each parameter adaptively so that the updating direction and step size of each parameter can be close to the optimal solution to the greatest extent. Adam's algorithm formula is as follows:

$$g_t = \nabla_\theta f(\theta_{t-1}) \tag{2}$$

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \tag{3}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \tag{4}$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \tag{5}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{6}$$

$$\theta_t = \theta_{t-1} - \frac{\alpha \hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{7}$$

where g_t is the grad at time t, ∇_θ represents the gradient of the parameter θ, θ_t is the parameter vector at time t, and $f(\theta_{t-1})$ is the value of the objective function at parameterv θ_{t-1}; β_1 is the exponential decay rate of the first moment estimate, and β_2 is the exponential decay rate of the first moment estimate m_t and v_t respectively represent the first-moment estimation and the second-moment estimation of time t; $\hat{m}_t$ and $\hat{v}_t$ is the result of correcting the deviation of the first and second order moments to prevent the estimation deviation of the first and second order moments from being large when t is small. α is the learning rate, and ϵ is a small constant used to prevent the denominator is zero.

3.5. Improved Adam algorithm

In this paper, the learning rate attenuation strategy is introduced based on the Adam algorithm, which can accelerate the updating speed of parameters, accelerate the convergence speed of the Adam algorithm in the early stage, and improve the accuracy of the model. The method of fraction attenuation is adopted in this paper, and the formula of fraction attenuation is:

$$alpha_t = \frac{alpha_{t-1}}{1 + decayrate \times epoch} \tag{8}$$

where $epoch$ stands for training rounds; $decayrate$ is the decay rate; $alpha_t$ is the current learning rate.

3.6. Prediction performance evaluation

Mean absolute error (MAE), mean absolute percentage error (MAPE) and mean square error (MSE) [10] were chosen as evaluation metrics to assess the prediction performance of the model quantitatively. The smaller the calculated error index, the smaller the difference between the predicted result and the actual value, and the more accurate the predicted result. Its formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{10}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{11}$$

where n is the amount of data, $\hat{y}$ is the predicted value of the model, and y is the real data.

4. Algorithm Flow

The neural network is optimized by the enhanced Adam algorithm in this paper. The data is fitted by repeatedly training the neural network. As the number of iterations increases, the learning rate will attenuate in fractional attenuation, and the optimal global solution is sought through the attenuated learning rate. This method aims to reduce the oscillation of the convergence curve in the iterative process and speed up training and convergence.

The main steps of load forecasting are as follows:

4.1. Load Data Preprocessing

The abnormal values and missing values in the load data are processed, and the load data is normalized.

4.2. Data Partitioning

The pre-processed dataset is divided into two parts: the training dataset and the test dataset.

4.3. Build a Prediction Model

According to the requirements of load forecasting, the input data dimension, output data dimension, and historical data length are determined, the model structure is selected, and the corresponding model is constructed.

4.4. Model Training

The training samples divided in the second step are used to train the load forecasting model, and the improved Adam is used to speed up model training. When the predetermined rounds or accuracy are reached, the training is stopped, and the model is saved.

4.5. Load Forecasting

The load forecasting model in step 4 is used to predict the samples in the test data. The model output value is the load forecasting result.

4.6. Prediction Results in Processing and Evaluation

The prediction results are obtained through reverse normalization, and the prediction results and actual values are calculated through the evaluation index calculation formula to obtain various evaluation indexes.

4.7. Model Evaluation

Various model evaluation indexes calculated in the previous step were used to analyze the errors between the test data set in Step 6 and the load prediction results, and the prediction model was evaluated to get a real evaluation.

5. Model Verification and Application

5.1. Data Selection

This paper uses the power load data of a light industry enterprise in eastern China from September 2022 to November 2022. The five-dimensional features of historical load, working day, month, temperature, and time-of-use electricity price are selected as input features.

5.2. Data Normalization

The linear normalization method mentioned above constrains the original data X in the range [0, 1].

5.3. Dividing training set and test set

The electricity consumption data from September 15, 2022, to October 15, 2022, was used as the training data set, and the electricity consumption data from October 15, 2022, to October 25, 2022, was used as the test data set.

5.4. Experimental Setting

In this experiment, to test the effect of the Adam-LSTM neural network for electricity consumption prediction, all information from the previous day is used as a historical feature of the current power load value on the 15-minute scale. The past load data and the characteristics of influencing factors were used as input variables of the model, so the input layer contained 5×96 neurons. The output layer is one neuron. We set the starting learning rate to 0.001, the hidden neuron of the LSTM module was set to 32, and we set LSTM to a three-tier result. The parameters of the small batch random gradient descent (SGD) model were optimized by an improved Adam optimizer, and the model is trained with standard mean square error as the target and implemented in the PyTorch framework.

5.5. Model Training and Optimization

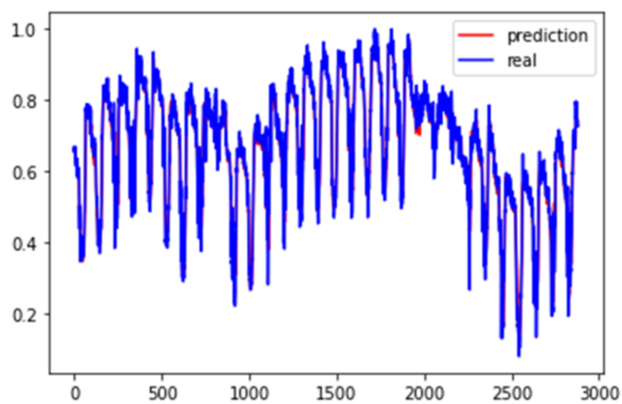

Figure 2. The prediction model's performance on the training set, the fitting effect, is better

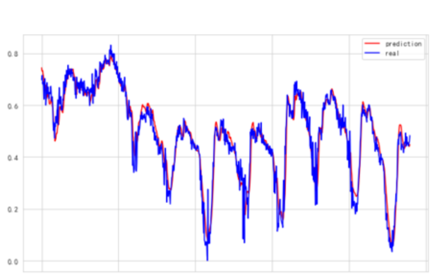

Figure 3. Comparison of forecasting results and actual values from October 15 to 25, 2022

Figure 4. Comparison of forecasting results and actual values on October 16, 2022

Table 1. Error evaluation of prediction results

	MSE	MAE	MAPE
Training sets	0.0014	0.285	3.12%
Testing set	0.0018	0.315	5.22%

In the figure above, the horizontal axis represents the sampling time point, and the vertical axis represents the normalized value ,the curve of the actual value and the curve of the predicted value are shown in the figure above by the blue and red lines, respectively. Figure 2 shows the effect of the trained predictive model on the training set. Figure 3 and Figure 4 show that this Adam-LSTM model considering the incentive mechanism has better prediction result in the whole process. One-step predictions based on the historical characteristics of the past day work better. The predicted value is the same as the actual value. Table 1 is the error evaluation of prediction results. The absolute error is also small. It can effectively predict short-term load changes, and the predicted data is closer to the true value. Through analysis, the model has high prediction accuracy, good stability, and feasibility.

6. Conclusion

To further enhance the precision of industrial and commercial load prediction, this paper takes into account the impact of incentive adjustment on the electricity consumption behavior of industrial and commercial customers, uses time-of-use electricity price as the influencing factor, and puts forward a short-term load prediction model based on Adam algorithm to optimize LSTM neural network, and applies the learning rate decay strategy. The improved Adam algorithm can adjust the learning rate automatically. Moreover, the Adam algorithm can ensure that the gradient of the previous update is not much different from that of the current update when the model is updated every time during the training process. The gradient is smooth and stable and can adapt to the unstable objective function. Through the simulation results, the proposed method has high prediction accuracy, with a mean absolute percentage error (MAPE) of 3.12% on the training set and 5.22% on the test set.

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