Short-term Load Forecasting of Power System Based on Improved Feedforward Neural Network

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Abstract. Short-term load forecasting of power system is the foundation of safe and stable operation of power grid, at present, short-term load forecasting of power system is easily affected by external features, so it is difficult to extract load data features accurately. Aiming at the problem of nonlinear, high-dimensional and poor generalization ability of load data, the short-term load forecasting method based on flower pollination algorithm and feedforward neural network is proposed. Flower pollination algorithm is used to optimize the combination of feedforward neural network weight threshold to reduce the error and improve the robustness of the algorithm. Finally, the prediction results of similar algorithms and those of the proposed method are compared through prediction evaluation indexes. After comparison, it is found that the method in this paper can effectively improve the accuracy of load prediction, which is conducive to increasing the safety and economy of power grid.

1. Introduction

The accurate and reliable load prediction model can effectively improve the safety and stability of power system. Load forecasting is a necessary condition for making power grid operation plans, which can also reduce resource waste and improve economic benefits [1]. With the access of a number of new types of electrical equipment, the distribution network covers a wide range and has a large amount of data. Therefore, fast data processing is not only suitable for the traditional load prediction method, but also in line with the idea of big data parallel processing [2].

At present, short-term load forecasting methods include statistical model, artificial intelligence and fuzzy logic [3]. However, the prediction value of the above model is single, so it can not provide comprehensive load information for the dispatcher. In literature [4], deep neural network and deep boltzmann machines are applied to short-term load forecasting respectively to solve the nonlinear problem in large-scale load data. The prediction accuracy is improved compared with the shallow neural network, but the timing of load data is ignored. A hybrid model based on LSTM network and convolutional neural network is proposed in [5]. This method combines the characteristics of long-term
memory of LSTM network and high-level data processing of convolutional neural network to process massive data and carry out short-term load forecasting. However, it is easy to lose the sequence information when the input time series is longer, so it is difficult to model the structure information between the data. In reference [6], a weather sensitive load forecasting method based on a new human comfort index is proposed. The multi granularity weather matching method is applied to urban residential power load forecasting; however, the accuracy of this method is not enough for high population density urban residents load forecasting, so it does not have universal applicability. In reference [7], the advantages of neural network and grey model are combined, and genetic algorithm is used to optimize, so as to complete short-term power load forecasting. But the training samples in this method are different from those of the date to be tested, which results in a long training time. In reference [8], the method of wavelet decomposition is proposed to project the load to different scales for prediction, so that higher prediction accuracy can be obtained. However, due to the limited prediction ability of BP neural network for high-frequency components, this method can not be used in the case of more impact load.

Flower pollination algorithm (FPA) is used to quickly optimize the key parameters of feedforward neural network (FNN) and establish a short-term load forecasting model. This method has the significant advantages. (1) FNN has simple structure, few control parameters and strong ability of approaching complex nonlinear relation. FPA-FNN can realize the dynamic transformation of global search and local search, improve the search ability of algorithm and avoid it falling into local optimum. (2) The training phase of the algorithm effectively reduces the requirements of prediction data, improves the prediction accuracy of neural network, effectively increases the operation safety of distribution network, and realizes energy saving and emission reduction.

2. Establishment of prediction model

Whether FNN can approach the target value accurately depends on the combination of weight and threshold and its network structure. However, in most cases, FNN tends to converge to the local optimal solution rather than the global optimal solution. So FPA is used to train FNN to improve its prediction ability. The short-term load forecasting process based on FPA and FNN is divided into two steps: training stage and testing stage.
There are three ways to train neural network with FPA: (1) The optimal combination of weight and threshold value is found by using flower pollination algorithm, which makes the calculation error of feedforward neural network smaller; (2) The optimal structure of feedforward neural network is found by using flower pollination algorithm [9]; (3) Using flower pollination algorithm to adjust the gradient learning parameters. In this paper, the first method is used to train the feedforward neural network.

FPA is a meta heuristic group intelligent optimization algorithm proposed by Yang, a British scholar, on the natural phenomenon of plant pollination in nature [10]. It is stipulated that both biological pollination and cross-pollination are considered as global pollination, and pollinators follow the Levy flight formula, while non-biological pollination and self-pollination are considered as local pollination. FNN has strong fitting ability to complex nonlinear data, good robustness and fault tolerance. But the choice of its weight and threshold will affect the final load forecasting time and the reliability of the forecasting results. Therefore, this paper uses FPA to train FNN to get the optimal combination of its weight and threshold, to shorten the prediction time and improve the local search ability of the algorithm.

In the process of FPA optimization, the transformation probability $p$ is introduced to realize the dynamic transformation of local search and global search for the population, update the pollen position and expand the range of population search, so as to prevent the population from falling into the local optimum.

3. FPA-FNN short term load forecasting process

The optimal combination of weights and thresholds in the training stage is taken as the combination of weights and thresholds of feedforward neural network in the test stage, and combined with the test data to the final prediction value. The overall short-term load forecasting process of FPA-FNN is shown in Figure 2.

**Figure 2.** Short-term load forecasting model
The purpose of the training phase is to find a combination of weights and thresholds to minimize the calculation error of the generalized regression neural network in the test phase. The specific steps of the training phase are as follows. (1) The parameters of flower pollination algorithm are initialized, and the population size $N$, iteration times, pollination intensity $\lambda$, step length and transformation probability $p$. (2) FNN parameter initialization, setting and initial values. (3) According to, we can judge whether to use local or global pollination. The combination is taken as the weight and threshold value of the generalized regression neural network in the training stage. The fitness function is used to determine whether to update the optimal combination of and. (4) The combination of and is continuously updated until the last set of data is trained or the maximum number of iterations is reached. (5) After the output of the optimal combination, the optimal combination is matrix coded to obtain the matrix of the optimal weight and threshold.

4. Simulation analysis

4.1. Comparative analysis
In order to prove the effectiveness of the proposed method, this paper uses the eight week load data collected by a power supply bureau to simulate and analyze the power load of the busy commercial district. Among them, the first six weeks of data as training data, the seventh week of data as forecast data, to predict the eighth week of busy business district load situation. The parameter settings of each specific algorithm are shown in Table 1.

### Table 1. Parameter setting for each method

| Method                        | parameter                  | numerical value |
|-------------------------------|----------------------------|-----------------|
| support vector machine        | $\gamma$                   | 0.0281          |
|                               | $\varepsilon$              | 0.001           |
|                               | $C$                        | 5.1             |
| RBFN                          | Learning rate              | 0.05            |
|                               | Iteration                 | 8000            |
|                               | Population size            | 22              |
|                               | Iteration times            | 900             |
| flower pollination algorithm  | Conversion coefficient     | 0.1             |
|                               | Size of step               | 1.7             |
|                               | $p$                        | 0.8             |

In order to verify the accuracy of this method, the RBFN method and the short-term load forecasting method in reference [11] are compared with this method.

As shown in Figure 3, in order to show the effect of FPA-FNN in load forecasting is more clearly, three prediction curves are fitted with the actual prediction curve. After comparison, it is found that FPA training neural network method has better tracking performance and smaller deviation to the actual load. Especially in the first 20 hours when the prediction error is large, the deviation between the prediction result of FPA training neural network method and the actual load is the smallest.
Figure 3. The actual load compare with the three methods

4.2. Forecast performance index

The accuracy evaluation of load forecasting mostly takes the index describing the error between the predicted value of load and the actual value as the evaluation index of the model. The smaller the error, the closer the forecast value is to the actual value, the better the prediction effect. In order to determine the accuracy of load forecasting and avoid the mutual offset of deviations, the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) are used to explain the accuracy of forecasting.

The results of the three prediction methods are shown in Table 2. It can be seen that the third error values are the smallest and FPA-FNN has higher fitting degree and prediction accuracy for load data.

Table 2. The evaluation of prediction methods

| Method   | MAE(MW) | MAPE% | RMSE |
|----------|---------|-------|------|
| RBFN     | 3.12    | 3.52  | 2.14 |
| SVR      | 1.85    | 2.21  | 1.95 |
| FPA-FNN  | 1.04    | 1.41  | 1.73 |

5. Conclusion

In order to achieve high accuracy and low error of short-term load forecasting results, this paper proposes a short-term load forecasting method based on flower pollination algorithm and feedforward neural network. By using the dynamic transformation of global search and local search of flower pollination algorithm, the search range of the algorithm is increased to avoid falling into local optimum. FPA is used to train FNN to get the optimal combination of weight thresholds, which improves the performance of the algorithm, improves the convergence speed and optimization accuracy, increases the security of power grid operation, and realizes energy conservation and emission reduction. Finally, the simulation analysis is carried out by using the actual power load data of a busy commercial district, and the method in this paper is compared with SVR and RBFN. The prediction evaluation index can directly reflect that the proposed method can obtain higher prediction accuracy, and has more extensive application potential.

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References

[1] Yang XS. Flower pollination algorithm for global optimization[J]. Unconventional Computation and Natural Computation, 2012,24(12): 240-249.

[2] Logenthiran, T., Srinivasan, D., Shun, T. Z. Demand side management in smart grid using heuristic optimization. IEEE transactions on smart grid, 2012,3(3):1244-1252.

[3] Kong Xiangyu,Zheng Feng,E Zhijun,et al.Short-term load forecasting based on deep belief network[J].Automation of Electric Power Systems,2018,42(5):133-139.

[4] Lu Jixiang,Zhang Qiwei,Yang Zhihong.Short-term Load Forecasting Method Based on Hybrid CNN-LSTM Neural Network Model[J].Automation of Electric Power Systems,2019,43(6):1-7.

[5] Gao Yajing,Sun Yongjian,Yang Wenhai.Weather-sensitive load's short-term forecasting research based on human body[J].Proceedings of the CSEE,2017,37(7):1946-1955.

[6] Ceperic E, Ceperic V,Baric A. A strategy for short-term load forecasting by support vector regression machines[J]. IEEE Trans Power System,2013,28(04):4356-4364.

[7] YU F,XU X.A short-term load forecasting model of natural gas based on optimized genetic algorithm and improved BP neural network[J].Applied Energy,2014,134(1):102-113.

[8] De Felice M, Xin Y. Short-term load forecasting with neural network ensembles: a comparative study[J]. IEEE Comput Intelligence Magazine,2011, 6(03):47-56.

[9] Amer D. On the performances of the flower pollination algorithm: qualitative and quantitative analyses[J]. Applied Soft Comput,2015, 34(07):349-371.

[10] Wang Xin,Meng Lingling.Ultra-short-term load Forecasting based on EEMD-LSSVM[J]. Power System Protection and Control,2015,43(1):61-66.

[11] Amer D. On the performances of the flower pollination algorithm: qualitative and quantitative analyses[J]. Applied Soft Comput,2015, 34(07):349-371.