The Application of Elman Neural Network in Uninterrupted Maintenance of Power Grid

Minggui Cao¹, Aidong Xu², Yixin Jiang², Qianru Wang¹, Zhen Wang¹, Yunan Zhang² and Hong Wen¹

¹School of Aeronautics and Astronautics, University of Electronic Science and Technology of China (UESTC), Chengdu 611731, China
²Electric Power Research Institute, China Southern Power Grid Co., Ltd. Guangzhou, China
*Corresponding Author Email: caominggui@std.uestc.edu.cn

Abstract. Uninterrupted Maintenance of power grid is the development direction of power grid. Electricity load forecasting is the basis for non-stop maintenance and the key to power grid load migration. Therefore, this paper analyses the plans and requirements of non-stop maintenance and predicts the grid load based on the Elman algorithm, by which the load forecasts are given. A load migration model is proposed, which can select the optimal low-load area in all areas to meet the business needs of non-stop maintenance.

1. Introduction
The main task of the distribution network is to provide users with uninterrupted power supply services [1]. In the wake of the development of cities and economy, modern society and cities have become more and more dependent on electricity demand, and the requirements for the quality of power used are also getting higher and higher [2]. Power supply companies need to continue to provide users with sufficient and stable power supply. Reducing the time of equipment outages and user outages caused by the improvement of the power grid operation level and maintenance status is the main direction of the power grid development. Non-power-off maintenance is a common practice in international advanced enterprises for the purpose of realizing users' uninterrupted power supply [3]. Through the bypass operation method, the power load of the area that needs to be overhauled can be moved to other areas, so as to realize the non-power-off overhaul of the distribution station [4].

This kind of uninterrupted maintenance has brought new technical requirements [5]. When the load is transferred, it is necessary to move the electricity load of the area to an area with a significantly lower load rate and monitor the electricity consumption of the distribution station and busbar. Once there is an overload possibly, move to other areas with low load rates in advance. This requires analyzing the electricity consumption and load conditions of each area and predicting future electricity consumption and load bearing conditions [6].

This article aims to solve the shortcomings of the existing technology, offer a short-term power load forecasting method in non-stop maintenance, and provide a migration plan based on the forecast data [7]. This method uses the Elman neural network model, which has stronger stability and forecasting performance than the time series model, and has a certain improvement in the accuracy of load forecasting.
2. Load Migration Model

After considering the load migration of the inspection area, the new area load cannot exceed the maximum load of the area, and the average load within the total time point of the inspection is as small as possible. The following mathematical model is established. The objective function is:

$$ \text{min}(F) = \min \left( \sum_{i=j}^{k} f \left( \frac{(A_i + B^n) - \text{Total}_{\text{Min}}}{\text{Total}_{\text{Max}} - \text{Total}_{\text{Min}}} \right) \right) $$

subject to:

$$(A_i + B^n) \leq \text{threshold}_n \quad n = \{1, 2, 3,...\}$$

Among them, $\text{Total}_{\text{Max}}, \text{Total}_{\text{Min}}$ is the maximum and minimum load during the load migration time period, $A_i$ is the electricity load forecast data in the maintenance area, $B^n$ represents the $n$ alternative electricity load forecast data in the area, and the function $f(x) = x^2$ will be normalized. The electricity load is mapped to different values, the greater the load, the greater $f(x)$. $j$ is the time when the load migration starts, and $k$ is the time when the overhaul ends and the load is cancelled. $\text{threshold}_n$ is the maximum load that the $n$th area can bear.

3. Elman Neural Network Principle

First of all, Elman neural network is an obvious non-static recurrent neural network. Its basic structure is similar to the neural network structure of traditional BP algorithm. It adds a new receiving layer in the hidden layer, and the delay operator is the receiver layer, so as to achieve the purpose of memory optimization. This memory optimization function can make our system have the ability to automatically adapt to the data set, and also bring the ability of time-varying characteristics. It makes the global stability of the algorithm network more stable. The calculation ability of common feed forward neural network is not as good as that of this algorithm, and the problem can be solved quickly [8].

3.1. Network Structure

Elman neural network is widely used, its neural network model is a very common feedback network [8]. Its structure can be divided into four layers: the first layer is the input layer, the hidden layer is in the second layer, the third layer and the fourth layer are the bearing layer and the output layer respectively. The connection of the first layer and the second layer is similar to the feed forward network [9]. We input the signal from the first layer, and the fourth layer can output the neural unit weighted. The activation function functions of the second layer of neural units can be divided into two types, one is linear, the other is nonlinear, and the other is nonlinear [10]. These structures increase the performance of algorithmic network in dealing with dynamic information and can be used for dynamic modeling [11]. Figure 1 shows the structure of the algorithm:
3.2. Learning Process
As shown in Figure 1 above, the nonlinear space of Elman algorithm is represented by the following formula:

\[ y(k) = g(w^3 x(k)) \]  
\[ x(k) = f(w^3 x(\cdot(k)) + w^2 (u(k-1))) \]  
\[ x_{\cdot}(k) = x(k-1) \]

In the formula, \( y \) is output node vector, and the dimension of this vector is the \( m \) dimension, \( x \) is the middle layer’s node vector, and the dimension of this vector is \( n \) dimension, \( u \) and \( x_{\cdot} \) are input and feedback vectors with \( R \) and \( N \) dimensions respectively. The parameter of the connection weight is set to \( w^3 \), \( w^2 \) and \( w^1 \) are also weight values, which belong to input layer to middle layer and bottom layer to middle layer respectively. As a linear combination of the output of the intermediate layer, \( g(\cdot) \) is the transfer function of the output neuron. \( f(\cdot) \) is often replaced by s function, which exists in the middle layer of neurons and is also a transfer function [12].

Elman neural network uses BP algorithm to correct weights, and the sum of square error function is used as learning index function [13].

\[ E(w) = \sum_{k=1}^{N} (y_k(w) - \hat{y}_k(w))^2 \]

4. Performances

4.1. Elman Algorithm Performance Analysis
Taking the historical electricity load data of the whole area of Jiangsu Province on December 10, 2018 as the prediction object, the Elman neural network is used to build the model. The training samples of the network use the electricity load data from December 1 to December 9, 2018. The data on December 10, 2018 is used as the test sample. The predicted actual value and predicted value are input in the same graph. Figure 2 uses Elman neural network prediction algorithm, Figure 3 uses BP neural network prediction algorithm, both calculation methods use the same training samples and parameters.
The prediction results of the two algorithms are shown in the table 1, where the prediction accuracy is represented by the average absolute error.

| Types of algorithms | Target error of training | Training times | Maximum absolute error(%) | Mean absolute error(%) |
|---------------------|--------------------------|----------------|---------------------------|-----------------------|
| Elman algorithm     | 0.001                    | 120            | 10.12                     | 2.51                  |
| BP algorithm        | 0.001                    | 124            | 12.28                     | 3.93                  |

In general, average absolute error is used to measure performance. Elman algorithm is superior to standard BP algorithm in this index, the accuracy is improved by 1.42%, and the maximum absolute error is also smaller than the standard BP algorithm, the maximum absolute error is reduced by 2.16%.
The results of the above simulation can show that the Elman algorithm has higher accuracy for load forecasting, which provides a guarantee for subsequent maintenance work without power failure.

4.2. Load Migration Example

The model is built using the Elman algorithm, and the training samples of the network used the electricity load data from December 1 to December 9, 2018, respectively for the three regions of Nanjing, Jiangyin, and Yixing, Jiangsu Province on December 10, 2018. The electricity load is predicted, and the load forecast result is shown in the figure.

![Forecast Data](image)

**Figure 4.** Forecast data

Assuming that the distribution station in Yixing City needs to be overhauled, through the load migration model proposed above and calculated according to the formula, we can transfer the load from Yixing City to Jiangyin City. Due to the grid data set, only a simple demo is provided. When there are more load areas, the load migration model will be more effective.

5. Conclusions

Uninterrupted maintenance is an important aspect in the development of power grids. Electricity load forecasting is the key to uninterrupted maintenance. Using Elman neural network algorithm to predict electricity load is an effective method. It has higher accuracy than standard BP neural network. Through the predicted power load, the load migration model put forward in this paper is used to realize the optimal plan for non-stop maintenance under the power grid.

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7. References

[1] H. Wen, PH Ho, C. Qi and G. Gong, "Physical layer assisted authentication for distributed ad hoc wireless sensor networks," *IET Information Security*, vol. 4, no. 4, pp. 390-396, December 2010.

[2] H. Wen, P. Ho and B. Wu, "Achieving Secure Communications over Wiretap Channels via Security Codes from Resilient Functions," *IEEE Wireless Communications Letters*, vol. 3, no. 3, pp. 273-276, June 2014.
[3] S. Chen et al., "Internet of Things Based Smart Grids Supported by Intelligent Edge Computing," IEEE Access, vol. 7, pp. 74089-74102, 2019.

[4] B. Ji, Y. Li, B. Zhou, C. Li, K. Song and H. Wen, "Performance Analysis of UAV Relay Assisted IoT Communication Network Enhanced With Energy Harvesting," IEEE Access, vol. 7, pp. 38738-38747, 2019.

[5] Aidong Xu, Qianru Wang, Yixin Jiang, Runfa Liao, Yunan Zhang, Yi Chen, Hong Wen, Jinran Du, "Quantitative selection of secure access policies for edge computing side terminals," ICICTA 2019, pp. 68-73.

[6] F. Xie et al., "Optimized Coherent Integration-Based Radio Frequency Fingerprinting in Internet of Things," IEEE Internet of Things Journal, vol. 5, no. 5, pp. 3967-3977, Oct. 2018.

[7] H. Wen et al., "A Cross-Layer Secure Communication Model Based on Discrete Fractional Fourier Transform (DFRFT)," IEEE Transactions on Emerging Topics in Computing, vol. 3, no. 1, pp. 119-126, March 2015.

[8] H. Wen, Y. Wang, X. Zhu, J. Li and L. Zhou, "Physical layer assist authentication technique for smart meter system," IET Communications, vol. 7, no. 3, pp. 189-197, 12 February 2013.

[9] Y. Xie, H. Wen, B. Wu, Y. Jiang and J. Meng, "A Modified Hierarchical Attribute-Based Encryption Access Control Method for Mobile Cloud Computing," IEEE Transactions on Cloud Computing, vol. 7, no. 2, pp. 383-391, 1 April-June 2019.

[10] L. Hu, H. Wen, B. Wu, J. Tang and F. Pan, "Adaptive Base Station Cooperation for Physical Layer Security in Two-Cell Wireless Networks," IEEE Access, vol. 4, pp. 5607-5623, 2016.

[11] L. Hu et al., "Cooperative Jamming for Physical Layer Security Enhancement in Internet of Things," IEEE Internet of Things Journal, vol. 5, no. 1, pp. 219-228, Feb. 2018.

[12] S. Chen et al., "A Novel Terminal Security Access Method Based on Edge Computing for IoT," International Conference on Networking and Network Applications (NaNA), Xi'an, China, 2018, pp. 394-398.

[13] X. Su, C. Pan, X. Yang and J. Zou, "Application of Elman Neural Network in Top Oil Temperature Prediction of Transformer," 2018 IEEE International Conference on High Voltage Engineering and Application (ICHVE), ATHENS, Greece, 2018, pp. 1-4.

[14] H. Wen, P. Ho and G. Gong, "A Novel Framework for Message Authentication in Vehicular Communication Networks," 2009 IEEE Global Telecommunications Conference, Honolulu, HI, 2009, pp. 1-6.