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Damage Calculation of Distribution Network Lines Relying on BP Neural Network

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Abstract: In order to better explore effective loss reduction methods and provide a basis for formulating scientific line loss indicators, this paper aims to study the distribution network (DN) line damage calculation relying on BP neural network. This paper makes an in-depth analysis of the existing non-destructive testing methods, and compares the advantages and disadvantages of various non-destructive testing methods in the home DN, such as low practicability, complex component distribution, and difficulty in collecting raw data. In addition, based on the analysis of the scientific method, management and various loss reduction measures of energy loss measurement, the current situation and existing problems of line loss measurement are analyzed from the perspective of line loss measurement data acquisition. In addition to bias methods and other aspects, this paper analyzes and summarizes research, especially bias measures, and provides many valuable insights from both technical and managerial perspectives. Experiments show that the simulation error is less than 1%. Compared with the traditional BP network, the learning rate of the algorithm in this paper is higher.

1. Introduction

In recent years, with the rapid development of the economy, my country's demand for industrial electricity has become larger and larger. In order to fully meet this demand, the power industry has continuously increased the amount of power supply and has also been greatly improved. On the one hand, the overall level of machinery manufacturing technology in the power industry is constantly rising, and China's electrical facilities technology has been significantly improved; on the other hand, the construction of the power grid has a more suitable plan, and the structure of the power grid tends to be rationalized, standardized and optimized. develop. However, the legacy problems of the domestic power grid construction over the years have also caused the power sector to face two major problems: one is how to basically ensure the safe and reliable operation of the power grid in the existing power grid; the second is how to ensure the economic operation of the power grid, reduce power grid losses and reduce power the company's operating costs. Therefore, reducing the line loss rate of the DN has always been an urgent problem for power companies to deal with. However, in order to formulate loss reduction methods and line loss audit standards, it is necessary to accurately calculate and analyze the line loss of the power grid to assist and guide. Management of line loss [1-2].

In the research of DN line damage calculation relying on BP neural network , many scholars have studied it and achieved good results, for example : Hartono J solves the problem from three aspects. Avoid getting stuck in local minima by adjusting the initial parameters, adjusting the number of hidden layers and default neuron weights. There is good experience with all three approaches and additional considerations should be considered during the application process [3]. Liu Z uses advanced initial weights and marginal memory methods this new advanced method can not only speed up network integration, but also improve the prediction accuracy of BP neural system [4].

First, this paper analyzes the current theoretical loss estimation methods in detail, and compares the advantages and disadvantages of various linear loss estimation methods. Secondly, for the power distribution system, the scale of automation is small, the distribution of components is complex, the number of components is large, the amount of data is large, and the acquisition of raw data is difficult. In this paper, a linear loss estimation method based on BP neural network is adopted, and a new version of the network is used to show the nonlinear complex relationship between linear loss and variable characteristics, as well as the evolution and linear transformation of the structure. Variables are preserved. Manual variable conversion error.

2. Research on Damage Calculation of DN Line Relying on Bp Neural Network

2.1. Application of Bp Neural Network in Damage Calculation of DN

But because these algorithms need to collect and organize more data, on the other hand, due to the fact that China's power distribution the system is minimally automated, with insufficient and backward measurements, making it difficult to collect the operational and structural parameters required for the calculations. This algorithm for improving energy flow is often difficult to implement, but there are many algorithms at home and abroad [7-8].

In recent years, the introduction and development of satellite networks have provided new ideas for the estimation of line losses in distribution systems. Therefore, such an algorithm does not need to obtain exact mathematical expressions of the input and output, and the matching of input to output can be done with example exercises. The data samples are first classified using a classification algorithm, then each group of data samples is mapped using a BP neural network, and the linear loss of the power distribution system is calculated. This method is simple and practical, but the BP algorithm is easy to reduce to a local minimum. The combination of genetic algorithm and BP model overcomes the shortcomings of ordinary BP algorithm, and is easy to integrate into the minimum local early genetic algorithm. The integration is not good, but the algorithm performance is complex. The radial basis function RBF (network) is theoretically capable of performing arbitrary actions, and the hidden part of the RBF network then determines the output weights using the BP algorithm or the least squares method. This method of determining output weights is also prone to falling into local minima, which affects the computational accuracy of the RBF network. However, online training takes a long time and the real-time effect is not good [9-10].

The BP algorithm divides the learning and training process of the BP neural system into two stages, namely expanding the input signal and increasing the inversion error signal. The first stage is the process of progress. At this stage, the network input signal is sent from the input layer to the hidden layer, and then to the production layer after the computational process of the hidden layer activation operation. The output layer emits the network response corresponding to the input signal. And correct and change the link weight and threshold of each layer[11-12].

2.2. Nervous System Application Process

In the process of using the BP system to design the line loss of the power distribution system, the original data should be processed to reduce the degree of inaccuracy of the data. The structure of the network should be determined, including the number of input points and the number of generating systems. On this basis, determine the appropriate training, prediction and online learning sample parameters, such as training speed, maximum number of iterations, margin of error, etc. Finally, online training is performed to determine the weights and closing prices, and used for prediction to reach the final result. Figure 1 below shows the process steps [13-14] :

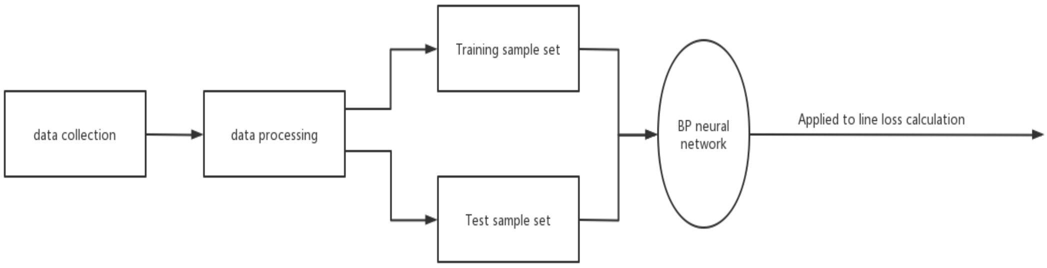

Figure 1. Line loss calculation scheme for DN using BP neural network

2.3. Technical Measures to Reduce Line Loss of DN

At present, many urban and rural DNs have complex networks. Due to long-term legacy problems, the automation level of the DN is low, the network layout is not optimized, the power supply capacity is insufficient, and the voltage is unstable. In recent years, power grid companies have increased investment in DN transformation, aiming to adjust network layout, improve power supply stability, and reduce line losses.

The approximate relationship between the power loss of each element of the power grid is [15-16]:

$$\Delta P = 3I^2 R = \frac{P^2 + Q^2}{U^2} \times R \tag{1}$$

To reduce the line loss of the DN, we can start from current and resistance. The main measures are described below.

The optimization of the network structure of the DN should be combined with the overall planning and layout of the city, and the length of the distribution line should be optimized as much as possible under the condition of meeting the electricity demand of users. The site selection and construction of the substation should be reasonable, the distance between the power source and the load should be reduced, and the number of circuitous power supply should be minimized. In addition, it is necessary to ensure that the voltage level of the grid meets the requirements. Assume that the percentage of increased voltage is

$$\alpha\% = \frac{U^{'} - U}{U} \times 100 \tag{2}$$

U, U'——the voltage before and after adjustment.

3. Research and Design Experiment of DN Line Damage Calculation Relying on Bp Neural Network

3.1. Matlab Simulation Platform

The platform used in this paper uses the MATLAB software of American MathWorks. The MATLAB programming method matches the thinking and expression of human scientific computing, making it difficult to learn. The programming process in MATLAB is similar to arranging formulas and solving problems in a spreadsheet. After more than 30 years of continuous development and improvement, the current version of Matlab has a variety of mathematical processing functions, including numerical calculations, matrix operations, graphics rendering, signal processing, file operations and so on. MATLAB data structure is based on arrays, compared with other engineering problems such as C and Fortran, MATLAB can save a lot of tedious point or matrix operations, and can save a lot of effort for the algorithm itself [17-18].

3.2. Experimental Design

This paper presents the analysis of the BP neural network designed in this paper. The first is to analyze the accuracy of the data simulation, by fitting the simulated data to the actual data results. Secondly, the improved algorithm for bP neural network in this paper. The superiority of the improved algorithm is determined by improving the data error under the same learning times.

4. Experimental Analysis on Damage Calculation of DN Line Relying on Bp Neural Network

4.1. Data Simulation

In this paper, the power consumption data of a battery user is selected for continuous simulation training of bp neural network. On this basis, the future power consumption of users in this area is analyzed, and the actual power consumption and the simulated data are analyzed and compared. The experimental data are shown in Table 1.

Table 1. Data simulation results

	1	2	3	4
Actual line loss rate	8.73	7.26	8.30	5.78
Calculate the line loss rate	8.73	7.20	8.56	5.96

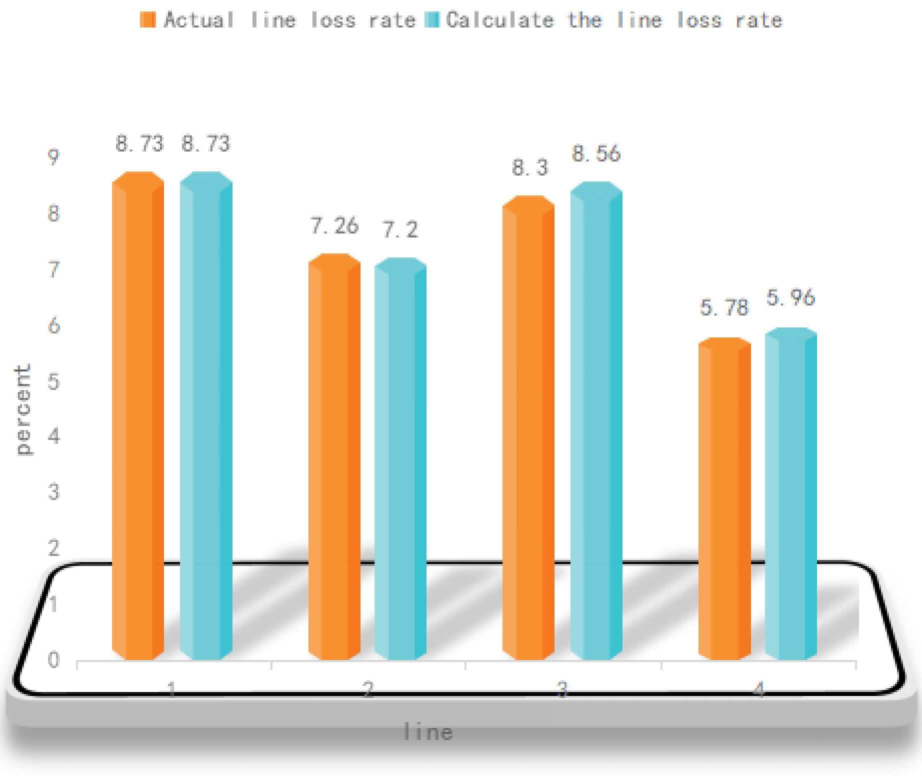

Figure 2. Error of actual line loss and theoretical line loss

It can be clearly seen from figure 2, through a period of learning, the neural network built for the area of user power simulation is more accurate, compared with the actual electricity consumption error is small, error basic control around 0.2, can effectively simulate part of the area of power simulation, to realize the effective distribution of power to a area.

4.2. Improve the Bp Network

This paper optimizes and improves the BP neural network, and compares the influence of the error with the learning times of the traditional original BP neural network. The experimental data are shown in Table 2.

Table 2. Comparison of the error changes between the two neural network algorithms.

	100	200	300	400
Initially the BP neural network	0.09	0.07	0.05	0.04
In this paper, the BP neural network of the	0.05	0.02	0.01	0.005

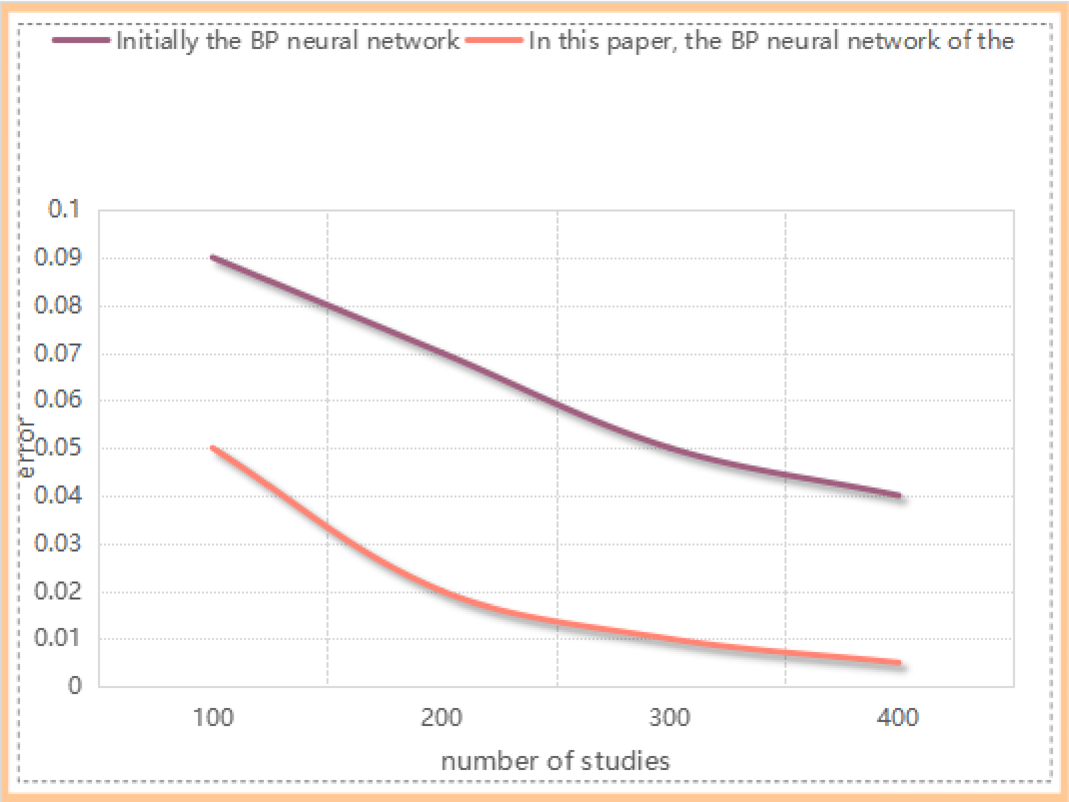

Figure 3. Effect of learning times on the error

It can be seen from Figure 3 that the error of the two BP neural networks is obviously smaller than that of the algorithm in this paper, and through multiple learning. The error of the algorithm in this paper is also smaller than that of the original neural network algorithm. And as the number of training increases, the error can be infinitely close to 0.

5. Conclusion

The tension of energy supply has become more and more obvious. Under the background of sustainable development, people pay more and more attention to the high efficiency of energy utilization. The use of electric energy is everywhere, and how to provide electric energy for the society more economically and reasonably is a major issue. Comprehensive and accurate theoretical line loss calculation work is of great significance. Therefore, this paper studies the line loss calculation and combines with specific practical examples. Through the analysis, the following conclusions are obtained: The research trend of line loss in DNs at home and abroad is analyzed. My country's DN has a large number of components and complex distribution. , the automation level is generally low, and the original data is not easy to collect, which makes some general DN line loss calculation methods have various shortcomings. The composition and classification of the DN line losses are explained, and the selection of the mathematical model of the DN is explained. The traditional DN line loss calculation method is analyzed, and various methods are compared. At the same time, from the technical measures and management measures, the methods of reducing line loss are summarized, which can provide reference for the actual work of reducing line loss. The definition of neural network is introduced, then four classical models of neural network are introduced, and they are compared, and the advantages and disadvantages of these four models are compared. Combined with the actual situation of this topic, BP neural network is selected as the computing power distribution model. A model of network line loss.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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