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Research Article

Predicting the Line Loss for a 10 kV Distribution Network Using AGA-BPNN

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With the rapid development of power grids, it is essential for these grid enterprises to pay more and more attention to the comprehensive reduction of power loss. Due to a large number of medium voltage power network based on distribution phenomenon nodes and power loss, it is difficult to collect accurate data of more than 20% of the total power loss of the network based on distribution phenomenon. Based on the above problems, it is significant to propose a method to quickly and accurately predict the losses in line of the 10 kV network based on distribution phenomenon. The improved BP neural network model and adaptive evolutionary algorithm programming can effectively analyze the 10kV transmission and distribution problems and reduce the line loss in the transmission project. The line loss prediction model mainly includes data cleaning, electrical characteristic index system, determination of the number of nodes in the BPNN hidden layer, and losses in line prediction. For this purpose, AGA-BPNN is proposed in this paper. Additionally, cable quality, power factor management, and reduction resistance are some parameters that can help lower the losses in lines. The author studies the performance of the losses in the line prediction model before and after the improvement of BPNN to validate the application impact of the AGA-BPNN algorithm in losses in line prediction of a 10 kV network based on distribution phenomenon. This technique has benefits of rapid convergence and great accuracy over ordinary BPNN. The simulation and computation of the example validate the suggested approach.

1. Introduction

The size of the network based on distribution phenomenon and the amount of power equipment rise in tandem with the economy. Because of its high proportion (more than 20%) in the entire power network grid, it is vital to decrease losses in the 10 kV network line based on distribution phenomena. In addition, due to the popularity of automatic data acquisition equipment, traditional losses in line computation methods are incapable of mining the relationship between vast amounts of data and losses in line. As a result, artificial intelligence algorithms are increasingly being utilized to assess 10 kV network based on distribution phenomenon losses in line. For this purpose, the selection of control parameters in genetic algorithms is essential. The 10 kV system has been used as a test subject. Different selection of control parameters will significantly impact the performance of genetic algorithms [1]. In the optimization process, crossover probability plays a leading role in the genetic operation. It controls the frequency of the crossover operation. A significant crossover probability can fully cross the generations of the population, but the possibility of destruction of the excellent model in the population increases, resulting in significant differences between the previous and subsequent generations, to make the search move towards aimless randomization. If the crossover probability is lower, the difference between generations is more negligible, so a continuous solution space is maintained. It also raises the chances of obtaining the best global answer. The second issue is that the rate of population evolution is too slow [2, 3]. If the crossover probability is too low, more individuals will be copied directly to the next generation, and the genetic search may be at a standstill [4]. An adaptive genetic algorithm (AGA) was proposed by Srinivas [5]. The basic idea is that the crossover and mutation probability can change with the change in fitness. When each individual's fitness in the population tends to be consistent or locally optimum, the crossover and mutation probabilities are increased to avoid slipping into local optimization, which results in an early phenomenon. When each individual's fitness in the population is somewhat dispersed, the crossover and mutation probabilities are lowered, killing the good and conserving the bad [6].

The power generation and transmission system transmits power to users through the network based on distribution phenomenon, and the network based on distribution phenomenon is directly connected to users at the end of the power network. Due to the characteristics of low voltage levels, aging equipment, and extended power supply radio, the losses in line of the network based on distribution phenomenon are more serious, accounting for more than 20% of the losses in line of the power network at each voltage level [7, 8]. In addition, due to the problems of many branches of 10 kV network based on distribution phenomenon lines, various load properties, incomplete historical data, and detailed losses in line statistics, the automation degree of a distribution system is relatively backward compared with the leading transmission network, and the detailed calculation parameters and data of losses in line are difficult to be accurately collected. However, the traditional theoretical losses in the line calculation method requires detailed network based on distribution phenomenon structure parameters, physical equipment parameters, and power grid operation parameters. This conventional approach necessitates a large labour and a lot of material resources, yet it has a low computation accuracy [9]. Therefore, how to accurately predict and evaluate the losses in line of a network based on distribution phenomenon has become the main influencing factor in identifying the losses in line of a network based on distribution phenomenon and provides a practical reference to the formulation of measures to reduce the losses in line of the network based on distribution phenomenon. It is one efficient method for reducing network line rate losses due to distribution phenomena and improving operational efficiency. The advantage of AGA-BPNN's weight and threshold method is that the weight and threshold of the traditional BP neural network (BPNN) to be optimized are globally searched for the optimal solution by AGA, and the optimal chromosome is reassigned to BPNN to obtain the trained network, which overcomes the shortcomings of the traditional gradient descent method. It is easy to fall into local minimum and slow convergence speed and improves the accuracy of losses in line prediction [10]. The examination of actual sample data from a 10 kV network based on distribution phenomenon in a given area reveals that the proposed technique has excellent validity, reasonableness, and practicability, according to the final results.

The rest of the research paper is organized as follows. Section 2 explains the AGA-BPNN, its initialization, adaptive variations, and other functions. Section 3 sheds light on losses in line prediction and its methodology. Section 4 contains the conclusion of this research.

2. AGA-BPNN (Adaptive Genetic Algorithm-Backpropagation Neural Network)

This section describes the AGA initialization, adaptive variation on crossover probability and mutation probability, AGA fitness function, and convergence conditions. AGA-BPNN model is used to predict the line loss of 10kV power grid. These functions will help explain the complete process of adaptive genetic algorithm-backpropagation neural network. The explanation is as follows.

2.1. AGA Initialization. Set maximum generation selection times of AGA as N. The weight and threshold of BPNN are encoded in real numbers to construct the chromosome of AGA, as shown in Figure 1.

Initialize the population K possessing P chromosomes. The P chromosome in the population i is P_i, $i \in [1, K]$, which constitutes a set of feasible solutions to the weight and threshold of BPNN.

$$D = n \times m + n \times l + n + l, \tag{1}$$

where n is the determined number of hidden layer nodes, m is the number of input layer nodes, and l is the number of output layer nodes.

2.2. Adaptive Variation on Crossover Probability and Mutation Probability. The traditional genetic algorithm adopts fixed crossover probability and mutation probability, which is not conducive to the population's diversity and the algorithm's convergence [11]. AGA is used to dynamically adjust the crossover and mutation probabilities with population evolution in order to represent the demands for optimization in different evolutionary periods and improve the algorithm's search efficiency and performance. The crossover probability P_c and mutation probability P_m change dynamically with the evolution of the population, as shown in the following equation:

$$\begin{gathered}
P_c = \begin{cases} \dfrac{P_{c1} - P_{c2}}{1 + K_c} + P_{c2}, & f \le f_{av}, \\ P_{c2}, & f \le f_{av}, \end{cases} \\
k_c = \exp\left(C\left(1 - \frac{2(f' > f_{av})}{f_{\mathrm{av}} - f_{\min}}\right)\right), \\
P_m = \begin{cases} \dfrac{P_{m1} - P_{m2}}{1 + K_m} + P_{m2}, & f > f_{\mathrm{av}}, \\ P_{m1}, & f \le f_{\mathrm{av}}, \end{cases} \\
k_c = \exp\left(C\left(1 - \frac{2(f > f_{\mathrm{av}})}{f_{\mathrm{av}} - f_{\min}}\right)\right),
\end{gathered} \tag{2}$$

where f is the fitness of the individual to be mutated, f_{av} is the average fitness of all individuals in the population, $f_{\min}$ is the smallest individual fitness in the population, P_{c1}, P_{c2}, P_{m1}, P_{m2}, and C are constants, P_{c1} is 0.9 or 1, P_{c2} is a constant

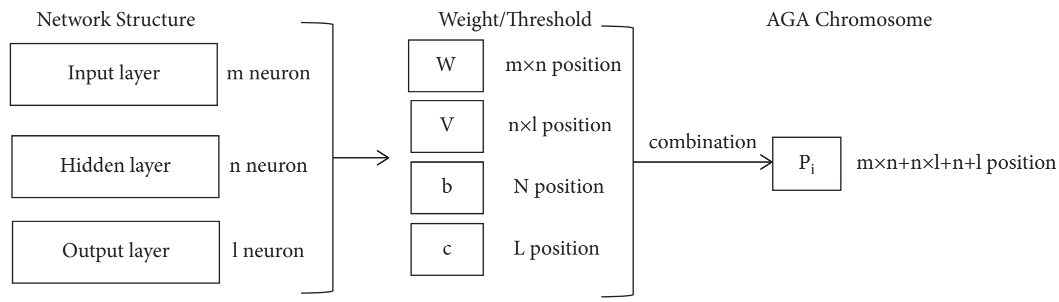

Figure 1: Chromosome structure of AGA.

in the interval $[0.5, 1]$, P_{m1} is 0.1, P_{m2} is a constant in $[0.05, 0.1]$, and C is 0.90.

2.3. AGA Fitness Function and Convergence Conditions. Set the total number of sample lines of the 10 kV network based on distribution phenomenon as$p$, j is one of the sample lines $j \in [1, p]$, the chromosome P_i (the weight and value of BPNN) optimized by AGA iteration is reassigned to BPNN to create the optimized network, and the losses in line evaluation value j of the line are gained after entering the electrical index data of the $\hat{y}_{ij}$ sample line. If the true value of the losses in the sample line is y_{ij}, the fitness function $F(i)$ of AGA is defined as

$$F(i) = \frac{1}{p}\sum_{j=1}^{p}\left(\hat{y}_{ij} - y_{ij}\right)^2 F_{\min} = \min(F), \tag{3}$$

where $i \in [1, K]$ and K are AGA population sizes, and the convergence criterion of AGA is set as follows:

$$F_{\min} \leq a, \tag{4}$$

where $F_{\min}$ is the mean square deviation from the losses in line evaluation value $\hat{y}_{ij}$ of AGA-BPNN algorithm and the actual losses in line value y_{ij}. The smaller the value of $F_{\min}$, the closer the algorithm's evaluation value for losses in line and the lesser the actual loss in line value.

2.4. AGA-BPNN Line Loss Prediction Model. According to the set fitness function F, the advantages and disadvantages of each chromosome of the population of the AGA algorithm are evaluated, and the selection, crossover, and mutation operations are carried out to realize the continuous evolution of the population [12]. The convergence condition of the AGA algorithm is that the chromosomes in the population meet formula (4) or the number of iterations of the algorithm reaches the set$N$. After the final optimization of AGA, the weights and thresholds that meet the set convergence conditions are assigned to BPNN to obtain the final AGA-BPNN losses in the line prediction model. Then, input the electrical characteristic index data on the test sample set into the established losses in line prediction model to obtain the losses in line evaluation value $\hat{y}_{ij}$. By comparing and assessing the relative error percentage of the losses in line evaluation value $\hat{y}_{ij}$, $\hat{y}_{ij}$ of the test sample set and the actual losses in line values y_{ij}, EC analyzes the prediction accuracy and calculation speeds of the losses in line prediction model.

$$\mathrm{EC} = \frac{\left|\hat{y}_{ij} - y_{ij}\right|}{y_{ij}} \times 100. \tag{5}$$

2.5. Losses in Line Prediction of 10 kV Network Based on Distribution Phenomenon. After the test of the step test sample set, the established 10 kV network based on distribution phenomenon losses in line prediction model has good prediction performance. The model can be applied to losses in line prediction. The electrical characteristic index data onto 10 kV losses in line with unknown losses in line are inputted into the losses in line prediction model to obtain the losses in line prediction value. The basic idea behind utilizing AGA-BPNN to forecast losses in line rate of a 10 kV network based on distribution phenomenon is to abstract the losses in line prediction problem of a 10 kV network based on distribution phenomenon from a regression analysis problem, take the electrical characteristic index as the independent variable of the regression analysis problem, and take the losses in line of 10 kV network based on distribution phenomenon as the dependent variable. Through AGA-BPNN learning of the training sample set and fitting the nonlinear relationship between the independent variable and the dependent variable to evaluate the online loss rate of the test sample set, the unknown online loss can be effectively predicted.

3. Losses in Line Prediction

This section explains the data cleaning, electrical characteristic index, determining the BPNN hidden layer nodes, and the improvement effect of AGA on BPNN. After analyzing all these parameters, we will be able to accurately predict the losses in lines. The complete explanation is as follows.

3.1. Data Cleaning. The original big data directly collected from the existing 10 kV network based on distribution phenomenon usually has the characteristics of incompleteness, inconsistency, and content fuzziness [13]. It is challenging to meet data analysis requirements of reducing losses in line and energy saving in the network based on distribution phenomenon. Therefore, it is necessary to clean the original data to improve the data quality and ensure the reliability of data analysis. Abnormal conditions in the process of data acquisition may lead to abnormal data. It will cause varying degrees of interference in the subsequent data analysis, resulting in inaccurate or even wrong data analysis. The data must be processed and cleaned [14, 15]. To more efficiently and reliably enhance data quality and validate the beneficial impact of BPNN, this paper uses the data cleaning method based on K-nearest neighbor to clean the data collected from the 10 kV network based on distribution phenomenon and verifies the effect of data cleaning with the actual data. The data cleaning designed by the author includes four steps.

(i) The first step is to check the dataset and eliminate the duplicate data onto the dataset, to reduce the data analysis workload.
(ii) The second step is the data integrity test to improve the accuracy of data analysis.
(iii) The third step is to check the validity and consistency of data to reduce the interference of unqualified data in data analysis.
(iv) The outlier detection algorithm based on the K-nearest neighbor is proposed in the final step.

3.2. Electrical Characteristic Index. After data cleaning, the error data, defect data, and outlier data in the original data are eliminated. The quality of experimental data has been dramatically enhanced to meet the requirements of algorithm verification. Using an existing 10 kV network based on distribution phenomenon as an example, the best electrical condition indicators in this paper are monthly active power supply, public transformer monthly active power supply, monthly reactive power supply, total capacity of the public transformer, and number of public sets with the most extended compact length [16]. These usual electrical indications are considered the AGA-BPNN input, and the losses in line of the 10 kV network based on distribution phenomenon are considered the AGA-BPNN output [17, 18].

3.3. Determining the Number of BPNN Hidden Layer Nodes. BPNN includes the input layer, hidden layer, and output layer. The input layer and output layer have only one layer. Once the research object is determined, the number of nodes is also determined; that is, the number of nodes in the input layer varies on the number of electrical condition indicators, and the number of nodes in the output layer is 1. The number of hidden layers and nodes is often challenging to determine. Theoretically, it has been demonstrated that a three-layer BPNN may approach any non-linear function with any precision. Considering the complexity of the network, one hidden layer is generally used. The selection of the number of hidden layer nodes is shown in Figure 2. Firstly, due to the stated problems, this paper uses the empirical formula to practically determine the proper number of hidden layer nodes and then uses the (x) cross method to further determine the number of hidden layer nodes combined with the actual data of a 10 kV network based on distribution phenomenon, using the following empirical formula:

$$n = \sqrt{0.43m + l + 0.12l^2 + 2.54m + 0.77l + 0.35} + 0.51\, n = n, \tag{6}$$

where n is the determined number of hidden layer nodes, m is the number of input layer nodes, and l is the number of output layer nodes. When calculating the value of n, round up n.

According to formula (6) and the number of electrical characteristic indexes adopted by a 10 kV network based on distribution phenomenon, the number of BPNN hidden layer nodes determined is

$$\begin{aligned} n &= \lceil 0.43m + l + 0.12l2 + 2.54m + 0.77l + 0.35\rceil + 0.51 \\ &= \lceil 0.43m + l + 0.12 \times 12 + 2.54 \times 6 + 0.77 \times 1 + 0.35\rceil + 0.51 \\ &= \lceil 4.86\rceil = 5. \end{aligned} \tag{7}$$

In the vicinity of 5 nodes in the hidden layer of 10kV distribution network, BPNN with different structures are used to learn and predict the sample data to find the best BP neural network structure. Figure 3 depicts the computation results.

As can be seen from Figure 3, for a 10 kV network based on distribution phenomenon, when the online evaluation error of BPNN is the smallest, the online prediction performance is the best. Therefore, the number of hidden layer nodes n is identified as 6; when n is greater than the determined optimal value, the BPNN losses in line prediction model are over-adapted. When n is less than the determined optimal value, the BPNN losses in line prediction model are under-fitted. In both cases, the losses in line evaluation error will decrease from the increase in the distance between n and the optimal value.

3.4. Improvement Effect of AGA on BPNN. In order to analyze the improvement effect of AGA on BPNN, three hundred and thirty lines of a 10 kV network based on distribution phenomenon are divided into a training sample set and a test sample set according to the ratio of 10 : 1 to satisfy the open set test criteria. Through comparative analysis, we found that AGA-BPNN had the smallest online loss. The results are shown in Table 1.

From the distribution of losses in line evaluation errors of test samples in Table 1, under different convergence criteria, the proportion of lines with losses in line evaluation

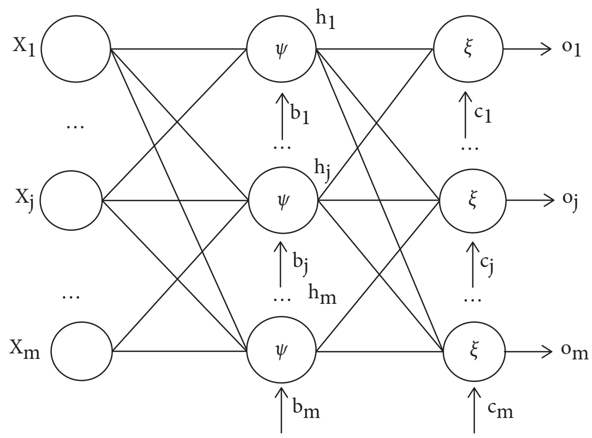

Figure 2: BPNN structure.

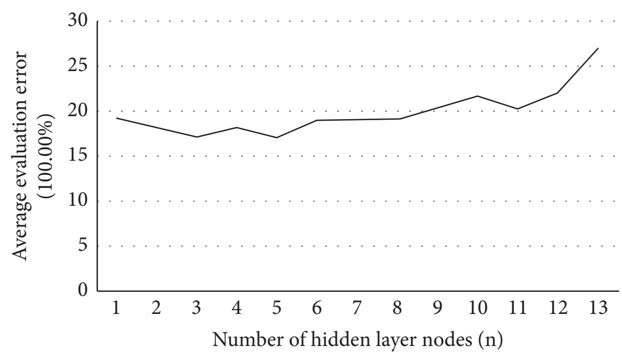

Figure 3: Relationship between the number of hidden layer nodes and the average prediction error.

Table 1: Evaluation error distribution of test sample set.

Prediction relative error *EC* (%)			EC < 5	5 ≤ EC < 10	EC ≥ 10
Convergence criterion ε	0.0035	AGA-BPNN	35	50	*15*
		BPNN	*20*	*20*	*60*
	0.004	AGA-BPNN	*40*	*20*	*40*
		BPNN	*15*	*25*	*60*
	0.005	AGA-BPNN	*45*	*15*	*40*
		BPNN	*20*	*15*	*65*
	0.006	AGA-BPNN	*25*	*45*	*30*
		BPNN	*20*	*10*	*70*

Table 2: Losses in line evaluation results of test sample set (unit: 10^4 kW · h/%).

Line number	Actual losses in line value	Losses in line prediction			
		AGA-BPNN		BPNN	
		Estimate	Error	Estimate	Error
No.14	2.523	2.523	2.504	0.75	2.835
No.18	5.488	5.488	5.438	0.91	5.121
No.59	2.215	2.215	2.394	8.08	1.578
No.67	3.054	3.054	2.995	1.93	3.602
No.115	3.896	3.896	4.106	5.39	4.437
No.136	3.156	3.156	3.150	0.19	3.370
No.212	2.476	2.476	2.457	0.77	2.631
No.244	0.703	0.703	0.619	11.95	1.014
No.269	0.773	0.773	0.800	3.49	0.991
No.294	0.571	0.571	0.552	3.33	0.852
No.326	0.768	0.768	0.674	12.24	1.046

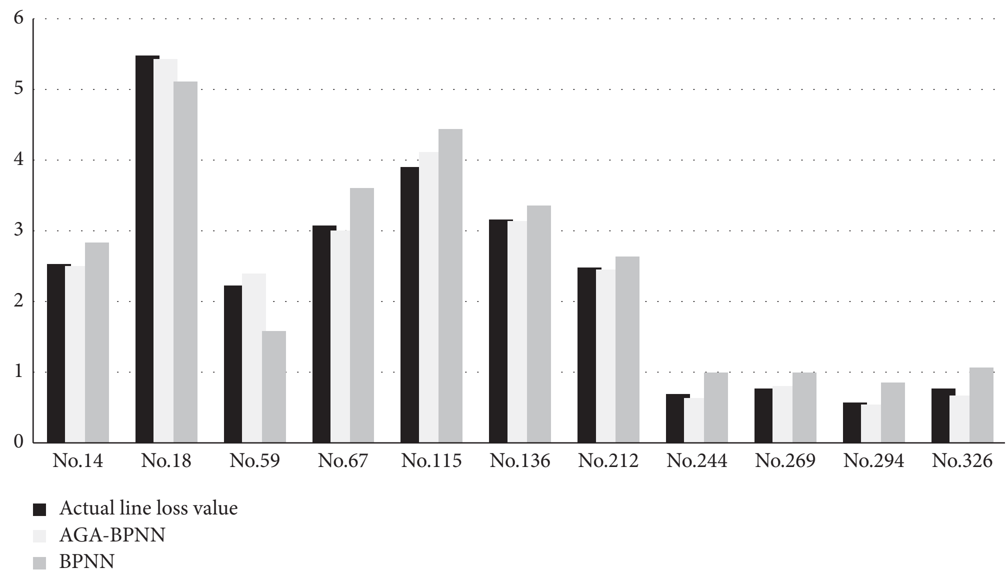

Figure 4: Comparison diagram of losses in line evaluation results of test sample set (unit: 10^4 kW · H/%).

error less than 5% AGA-BPNN is more significant. And AGA-BPNN with evaluation error greater than 10% is less than BPNN. Therefore, the overall accuracy of losses in line evaluation of AGA-BPNN is higher than that of BPNN. Taking the convergence criterion of 0.005 as an example, the losses in line evaluation results in AGA-BPNN and BPNN are further analyzed. Their average evaluation errors are 7.12% and 22.77%, respectively. The losses in line evaluation results of the test sample set are shown in Table 2 and Figure 4.

In Figure 4, the AGA-BPNN evaluation value is closer to the actual losses in line value as a whole, and the accuracy of the AGA-BPNN algorithm is higher.

4. Conclusion

In this paper, the isolated points in the original data are detected and eliminated by data cleaning technology, providing the groundwork for theoretical study into losses in line prediction in a 10 kV network based on distribution phenomenon. Then, the best electrical characteristic index of the 10 kV network based on distribution phenomenon is introduced as the input of AGA-BPNN, and the best network structure of BPNN is determined by using the cross-verification method, trial and error method, and actual data prediction verification. Based on the distribution phenomenon, the test sample set prediction results and the distribution of prediction results of a 10 kV network were analyzed, the better improvement effect of AGA on BPNN is verified, and the application effects of four standard neural networks in losses in line prediction of 10 kV network based on distribution phenomenon are compared and analyzed. Taking a 10 kV network based on distribution phenomenon as an example, it is found that AGA-BPNN has better accuracy and convergence. Finally, the AGA-BPNN method is applied to losses in line prediction to verify the practicability of the proposed method. It can be seen that this paper applies the proposed method of a 10 kV network based on distribution phenomenon and takes the line of unknown losses in line as an example to predict the losses in line, which has high practical significance.

At the moment, we should focus on various factors in AGA, such as population size, selection operator, chromosomal cod mode, and so on. The author employs the empirical findings of his investigation. Future research should investigate the influence of these factors on the optimization abilities of genetic algorithms in different populations and evolutionary stages, as well as the optimal values of these parameters under various scenarios. In addition, there is still much room for improvement in AGA. The author believes that it can be improved in the two cases of premature and local convergence. So far, there are mature methods of small-scale path analysis, but if there is a large population, the application of the current method will be limited, and there will be evolutionary stagnation or linear programming.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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