ESDD and NSDD of UHV DC Insulator online Prediction Using BP Neural Network

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Abstract
In order to find an effective method to online predict the ESDD and NSDD of the UHV DC insulators, this paper introduced a method using the genetic algorithm to optimize the initial weights and thresholds of the back propagation neural network (GA-BPNN) for the prediction of UHV DC line insulators' ESDD and NSDD. A predication model based on GA-BPNN with the online monitoring data of the UHV DC insulators was built to forecast the ESDD and NSDD. The experimental results showed the convergence speed and precision of GA-BPNN was better than that of conventional BPNN. The prediction results showed accurately in our study. The results proved that using the model based on GA-BPNN with the online monitoring data to predict the ESDD and NSDD is feasible.
Key words: ESDD, NSDD, ONLINE PREDICTION, GA-BPNN

1. Introduction

For many advantages, the ±800kV UHV DC power transmission lines are developed rapidly in China [1-4]. The line insulator is very important in power system. The insulator flashover is one major problem to the safety of power grid. The timing measurement and cleanout of the insulator pollution is the basic method which keep the power grid from the flashover. The insulator pollution measurement results usually can be expressed as Equivalent Salt Deposit Density (ESDD) and Non-soluble Deposit Density (NSDD), and the pollution conditions are important to the insulator flashover [5], which can lead to serious accident in power grid. Previous researches showed the pollution of DC insulators is much more serious than that of AC insulators [6, 7]. To realize the on-line monitoring of the UHV DC insulator's pollution is very important to power grid safety.

The leakage currents of insulator and the meteorological parameters, such as the temperature, humidity and so on, can be on-line measured, however, the insulator pollution measurement is done by manual work [8, 9]. Studies [10, 11] showed that the leakage current of insulator was strongly linked to the ESDD and the operation meteorological environment of the insulator. Therefore, the ESDD can be forecasted by the leakage current and meteorological parameters. However, the relationship among the leakage current, ESDD, and meteorological parameters is complex, so the prediction of ESDD and NSDD by the leakage current and meteorological parameters is a complex nonlinear problem. Some researchers have used the BP neural network to predict the ESDD [12]. The standard BP algorithm trains the weights and biases of neural network by the methods of gradient descent or conjugate gradient decent by calculating the partial derivative of the performance with respect to the weights and biases values. BPNN has been widely used in many fields. However, it has been proven that conventional BP algorithm has defects of slow convergent speed and easy convergence to a local minimum point of error function [13].It is necessary to overcome these flaws. And also, the data to build the model almost were from artificial experiments, which were different from the data in the operating conditions, so the results must be affected. Most of the studies only predicted the ESDD, but the NSDD is also closely linked to the flashover, so it is it is necessary to predict the NSDD.

The GA [13], in particular, has already been used to optimism the BP NN because of the global search characteristic. It has been employed the GA to optimize initial weight and threshold of the BPNN. There have been various efforts that combine GA with BPNN. For example this method was used for power transformer fault diagnosis [14], while for the blade pattern optimization [15], and for Short-Term Climate Prediction in [16].

In this study, we successfully built the predication model based on the GA-BPNN to forecast the ESDD and NSDD of UHV DC insulators as a new application. And all the data which built the model came from the on-line monitoring devices of the UHV DC insulators. So it is verified the model is accurate and consistent with the actual situation.

2. BP Neural Networks

A sample neural network includes three different layers: the input layer, the hidden layer and the output layer. BPNN is a multi-layer feed forward neuron network, and the BP algorithm includes two components: the forward propagation of information and the back propagation of error. The input layer is responsible for receiving information from the outside, and the input information which has been handled by the hidden layer unit is transmitted to the output layer; while the output layer is responsible for transmitting the result of information processing to the outside. If the result in the output layer is not ideal, the network will calculate the variation of errors and propagate errors back along the former route while correcting the weight. This process is repeated until it gets the satisfied result or it reaches the maximum number of iterations. Therefore, BP algorithm is also called as the back propagation of error. Although BP network has been widely used, it has serious flaws of slow convergence, prone to local minima, poor ge- neralization and etc.

3. Genetic Algorithm

Genetic Algorithm is a stochastic global searching algorithm used to solve complicated problems by simulating the evolutionary course of natural selection and natural inheritance of biology circles [9], [10]. In genetic Algorithm, code space is used to replace problem space, fitness function is regarded as evaluating criterion, code population is regarded as evolution base, selection and genetic mechanism is actualized by genetic operation on individual bit chain of population. A repeated course is formed in this way. The individual of population evolves ceaselessly by recombining some important genes of code bit chain stochastically, and approaches to the optimal gradually till reaching the goal of solving the problem ultimately.

The basic operation e of the GA can be described as follows:

1. Selection. During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected.

2. Crossover is a genetic operator used to vary the programming of a chromosome or chromosomes from one generation to the next.

3. Mutation is a genetic operator used to maintain genetic diversity from one generation of a population of genetic algorithm chromosomes to the next.

The basic elements of the GA include chromosome coding, fitness function, genetic operation and function parameters.

4. BP NN Optimized by the GA

The weights and thresholds of BP neural network were optimized by the GA, and then the prediction precision of the BPNN can be improved. The basic elements of the GA optimized BPNN include initialization, fitness function, the selection, the crossover, and the mutation.

(1) Initialization.

Firstly, chromosomes were initialized utilizing real-number encoding by numbering individual.

(2) Fitness function

The fitness function can be defined as follows:

$$F=\sum_{i=1}^{N}\sum_{j=1}^{C}abs\left(y_{ij}-o_{ij}\right) \tag{1}$$

Where, y_{ij} is real output of the network,

o_{ij} is the predicted output of the network

N is the total number of training samples,

C is the number of output neurons.

(3) Selection

In this study, the roulette method was the selection method. The individual selection probability Pi can be defined as follows:

$$f_i=k/F_i$$
$$P_i=\frac{f_i}{\sum_{i=1}^{N}f_i} \tag{2}$$

Where, F_i is the fitness of i_{th} individual , N is number of the population, k is coefficient.

(4) the crossover

The crossover of the ith chromosome ai and the jth chromosome a_j at the position k can be described as follows:

$$a_{ik} = a_{ik}(1-b) + a_{jk}b$$
$$a_{jk} = a_{jk}(1-b) + a_{ik}b \quad (3)$$

Where, b is a random number between 0 and 1.

(5)the mutation

The mutation of the j_{th} chromosome of i_{th} individual a_{ij} can be operated as follows:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g) & r \geq 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g) & r < 0.5 \end{cases} \quad (4)$$

Where, a_{max} and a_{min} is the upper and lower bound of a_{ij},

$f(g)=r_2(1-g/G_{max})$, r_2 is a random number, g is the current number of iterations, G_{max} is the largest number of evolution.

b is a random number between 0 and 1.

The working flow of GA-BPNN algorithm can be seen Figure 1.

The procedure of the GA-BPNN can be described as follows:

Step1: Initializing topology of BP NN according to the training sample set.

Step2: Normalization of the samples data

Step3: Initialize the evolution, population size, crossover probability, mutation probability

Step4: Calculate the fitness and find the best individual

Step5: To perform selection, crossover and mutation, until get the optimal initial weights and thresholds.

Step6: Taking the weights and threshold values which optimized by GA as the initial parameters, the BP network makes autonomous learning.

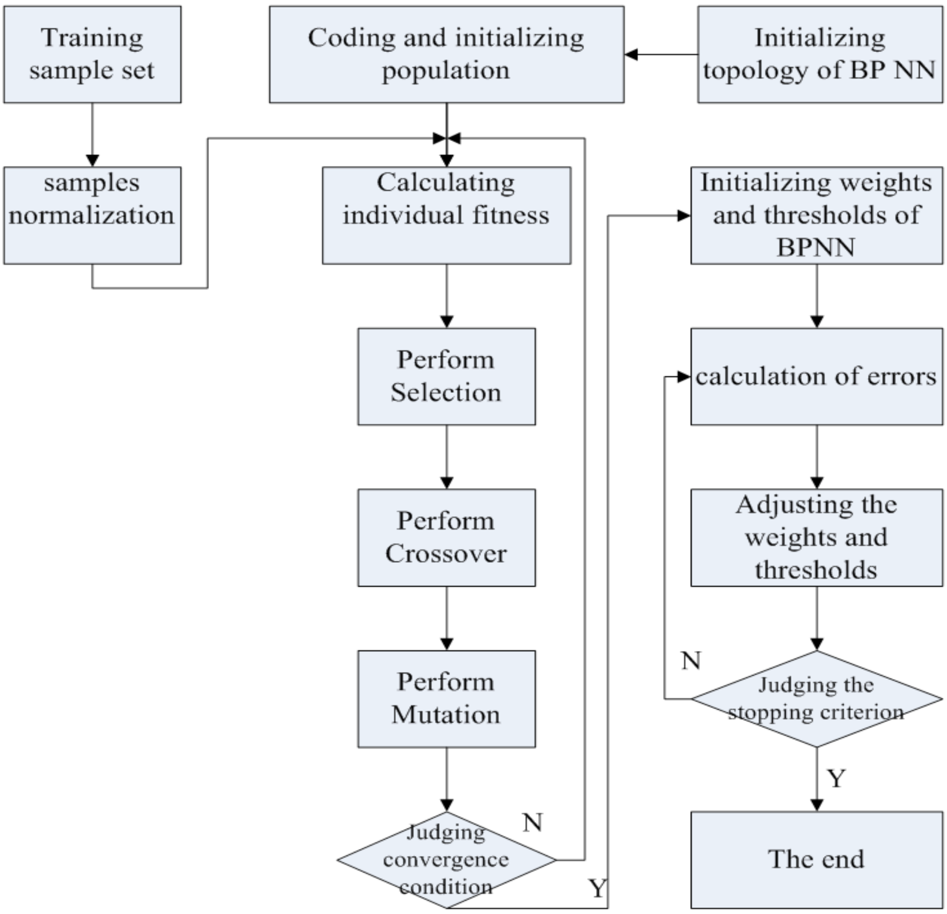

Figure 1. The working flow of GA-BPNN algorithm

5. Application in Predication of UHV DC Insulator's ESDD and NSDD

5.1. Model Setup

Previous studies [10-12] showed that the leakage current of insulator has close association with the temperature, relative humidity and the ESDD. And they selected the temperature, relative humidity and leakage current as the input units of BP neural network. And in our study, the dew point has been selected as one input units. So, we selected the leakage current, the temperature, relative humidity and the dew point as the input units, and the NSDD and ESDD of one porcelain UHV DC insulator was selected as the output units. The data of the leakage currents, the temperature, relative humidity and the dew point are synchronous. The on-line monitoring technology of the leakage current, the temperature, relative humidity and the dew point can refer to [8], and the measurement of the ESDD and NSDD and its results can refer to [9]. The data set includes 573 data points, of which 400 points were used to train the GA-BPNN and the rest will be used to test. The training data were collected on the day just before the ESDD measurement, and the test data were collection around the day on which the ESDD measured but not the day just before the ESDD and NSDD measurement. Because the insulator pollution accumulated very slowly, the ESDD and NSDD values changed very little in these days.

In this study, the BP neuron network has three layers including one hidden-layer. The neural networks models are trained with four neurons as input data while five neurons for the hidden layer, and two neurons for output layer. The neuron transferring function in hidden-layer is tansig, and that in output-layer is purelin. And the training function is traingdm. The training error precision is 0.0001.

The parameters of GA were selected as follows. The population size is 10, the maximum number of evolution is 10, the crossover probability is 0.3 and the mutation probability is 0.1.

5.2. The Results

The figure 2 shows the iterations of the BPNN without optimized and the performance of the GA-BPNN. The best training performance of the traditional BP neural network is 9.9997×10^{-5} at epoch 23779, and that of the GA-BPNN algorithm is less than 1×10^{-10} at epoch 10. So the GA-BPNN can greatly improve the training speed and precision.

The forecasting values of the ESDD and NSDD with GA-BPNN algorithm are shown in figure 3. From the figure 3, it can be seen that this method can forecast the ESDD and NSDD of insulators exactly. And the forecasting errors of this method are very little. In these figures, the forecasting values are close to the real values, and the relative errors are less than 0.5%. The results showed that the GA-BPNN algorithm is a good method for the forecasting pollution of UHV DC insulator in our study.

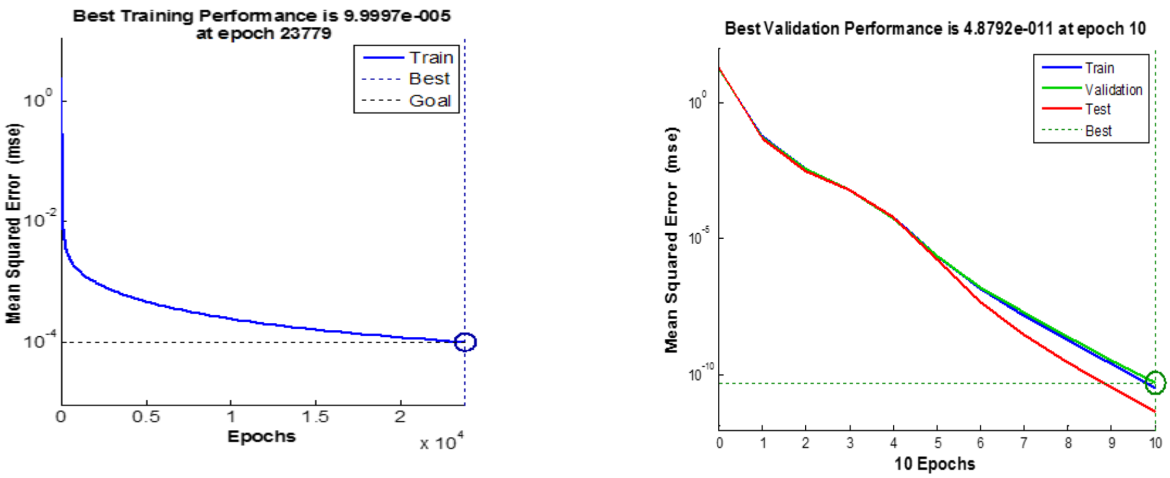

Figure 2. Convergence rate of the BPNN(left)and the GA-BPNN(right)

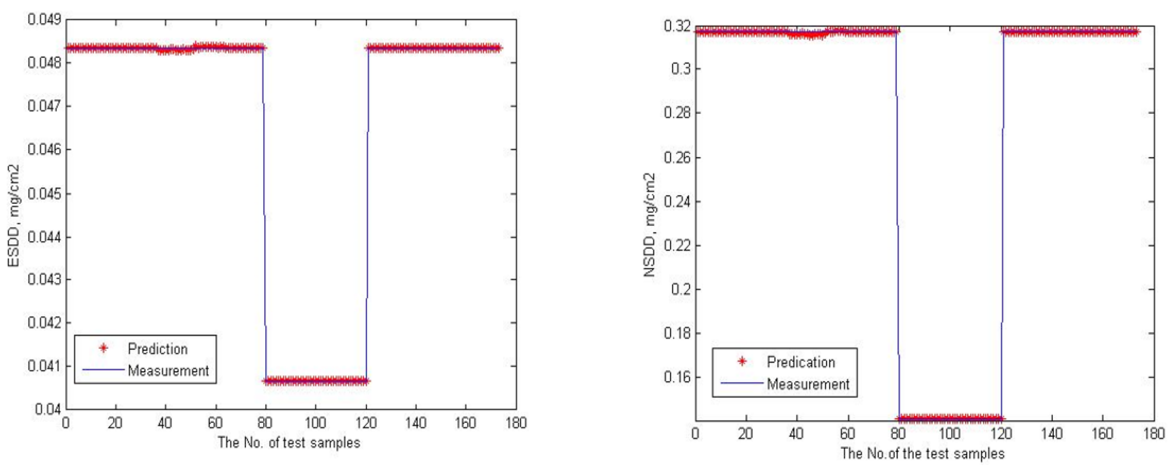

Figure 3. The forecasting results of the ESDD(left) and NSDD(right) with the GA-BPNN

6. Conclusions

In this paper, we have proposed a new application of the GA-BPNN algorithm to predict the ESDD and NSDD of the UHV DC insulators. A prediction model using the GA-BPNN was built and all the data came from the on-line monitoring devices of the UHV DC insulators. The convergence rate of the BP neural network had been greatly improved by the GA algorithm. The forecasting results showed perfect. The convergence speed and precision of GA-BPNN algorithm was better than that of conventional BP algorithm. Therefore, the ESDD and NSDD online prediction of UHV DC insulator based on the GA-BPNN algorithm will be used in the practical engineering in future.

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