Prediction model of insulator contamination degree based on adaptive mutation particle swarm optimisation and general regression neural network

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Abstract: The contaminants accumulated on the surface of transmission line insulator mainly come from the suspended particles in the air. Therefore, it is necessary to consider meteorological factors and environmental factors in the prediction of insulator contamination degree. In view of the advantages of generalised regression neural network (GRNN) in the aspects of fault tolerance and robustness, this study uses it to predict equivalent salt deposit density (ESDD). Furthermore, the adaptive mutation particle swarm optimisation and general regression neural network (AMPSO–GRNN) model is proposed in this study. According to adaptive algorithm and mutation algorithm, the inertia weight and acceleration factor of particles are dynamically adjusted to achieve the purpose of searching global optimal smoothing factor. The optimisation method can effectively avoid the premature convergence of particle swarm optimisation (PSO) and solve the drawback that PSO is easy to fall into the local optimal value. The results show that the prediction model proposed in this study can effectively predict the insulators ESDD, and the prediction error is less than the GRNN and PSO–GRNN models. The research can provide guidance for the development of a more scientific and rational maintenance plan to achieve effective control of the contaminants of the line.

1 Introduction

In recent years, China’s ultra-high voltage (UHV) transmission lines have been vigorously developed, which can provide reliable power guarantee for regional power grid. However, the insulator pollution flashover accidents may threaten safe and stable operation of power system [1, 2]. Among them, the investigations show that power outage accidents caused by pollution flashover account for 47% [3]. Pollution flashover accidents may result in lines out of running, loss-of-voltage in transformer substations, forcing power plant units to shut down and other serious consequences [4]. In addition, pollution flashover accidents have an important relationship with contamination degree. The more serious contamination degree is, the more likely pollution flashover accidents will occur. Thus, it is necessary to predict contamination degree in order to pollution flashover accidents. By predicting contamination degree, warning information can be issued early, and cleaning work can be done timely, and scientific and reasonable maintenance plans can be planned. Therefore, a new neural network prediction model is proposed in this paper.

The evaluation method for insulator contamination degree can be divided into two kinds: physical method and neural network method. On the one hand, the physical method is mainly based on the characteristic of contamination, such as insulator leakage current [5], insulator infrared image features [6], insulator ultraviolet image features [7], and measuring contamination degree based on optical sensor [8]. On the other hand, the neural network method predicts insulator contamination degree by establishing non-linear mapping relationship between input variables and output variables [9, 10]. Among them, the generalised regression neural network (GRNN) has a strong advantage in learning velocity, approximation ability, and classification ability. In addition, it has a great prediction effect when the sample data are lacking [11], so it has been widely used. In the GRNN, the smoothing factor parameter has a great influence on the performance of the network [12]. If smoothing factor is larger, the approximation process will be smoother, but the approximation error will be greater; and if smoothing factor is smaller, the prediction results will be contrary.

Therefore, choosing an appropriate smoothing factor value is a problem that GRNN network needs to be optimised.

The standard particle swarm optimisation (PSO) algorithm is used to calculate the population optimal solution, but it is easy to appear the phenomenon of aggregation [13], which makes it easy to fall into local extreme point and cannot get population optimal solution. Furthermore, the influence of inertia weight on the population and local search ability of algorithm is significant [14]. However, the inertia weight in the traditional algorithm is fixed and cannot be dynamically adjusted according to test date, which makes the algorithm less effective and the optimal solution is not ideal. At the same time, the learning factor also has a great influence on the search ability of the algorithm [15, 16]. Based on the above drawbacks, this paper optimises the standard PSO algorithm by judging the average particle distance and dynamically adjusting inertia weight in order to realise the adaptive and mutation function of the algorithm.

In this paper, the daily equivalent salt deposit density (ESDD) data were collected from the running line of Pingdingshan natural pollution test station in Henan by on-line monitoring equipment. Then, the GRNN prediction model optimised by adaptive mutation particle swarm optimisation (AMPSO) algorithm is established in order to predict ESDD value of insulator. The results show that the accuracy of proposed model is better than GRNN and PSO–GRNN models, so it is instructive to arrange scientific and reasonable maintenance plan for the running transmission line.

2 Data collection

2.1 Experimental environment

Pingdingshan city is located in the south-central part of Henan Province, China, which is in the warm zone. There is always south wind in spring and summer, while north wind in autumn and winter. Annual precipitation is ~1000 mm. The Pingdingshan natural contamination test station is located in the eastern suburb of Pingdingshan, built in 2004. According to polluted area distribution map, the polluted level around test station is E, and the...
main pollution sources are thermal power stations, fertilizer plants, stone factories, chlor-alkali plants, and steel plants. The on-line monitoring equipment is installed on no. 45 tower of Pingxu transmission line in test station, which is used to monitor ESDD values. On-line monitoring equipment is based on optical sensor. Fig. 1 shows the installation position diagram of monitoring equipment. The voltage level of Pingxu transmission line is 220 kV. According to on-line monitoring equipment, the daily ESDD values can be obtained, and this paper uses these data to validate the accuracy of proposed prediction model.

2.2 Monitoring equipment

The monitoring equipment is based on quartz glass rod. The schematic diagram of monitoring equipment is shown in Fig. 2, and the system diagram of on-line monitoring equipment is shown in Fig. 3. It is based on the theory of light field distribution in the medium and optical energy loss mechanism [8]. The monitoring equipment places a quartz glass rod in the atmosphere which is a multimode medium. If there is no contamination on quartz glass rod, optical waveguide in fundamental mode and high-order mode transmits light energy together, and most of light energy transmits at the core of quartz glass rod, but only a small amount of light energy transmits along the cladding layer of core package, which causes some light energy loss. If there is some contamination on quartz rod, the transmission conditions of fundamental mode and high-order mode in the optical waveguide will be changed. If there is more contamination, the loss of light energy will be more serious. Based on above theory, the contamination can be measured.

3 GRNN prediction model

GRNN is a new type of neural network proposed by Donald Specht [17]. Its structure is shown in Fig. 4, including input layer, model layer, summation layer, and output layer. The input data of network is \( X = [x_1, x_2, ..., x_n]^T \), and its output data is \( Y = [y_1, y_2, ..., y_k]^T \). \( n \) represents the number of input variables, \( k \) represents the number of output variables.

The number of neurons in the input layer is equal to the number of input variable in the learning samples, and each neuron directly transfers input variables to model layer.

The number of neurons in the model layer is equal to the number of neurons in the input layer \( n \), but each neuron in the model layer corresponds to different sample. The transfer function \( P_i \) of neurons \( i \) is

\[
P_i = \exp\left[-(X - X_i)^T(X - X_i)/2\sigma^2\right]
\]

where \( X \) is input variable of network, \( X_i \) is learning sample corresponding to the \( i \)th neuron, and \( \sigma \) is the smoothing factor of GRNN.

There are two types of neurons in the summation layer. The one \( (S_D) \) is the arithmetic summation of all output of neurons in the model layer, and the connection weights between each neuron in the model layer and each neuron in the summation layer are 1, and transfer function is

\[
S_D = \sum_{i=1}^n P_i
\]

The other \( (S_{ij}) \) is that neurons sum all outputs of neurons in the model layer by connection weight, and the connection weights between the \( i \) neuron in the model layer and the \( j \) neuron in the summation layer are the \( j \) element \( y_{ij} \) of the \( i \) output sample \( Y_i \), and transfer function of these neurons in the summation layer is

\[
S_{ij} = \sum_{i=1}^n y_{ij}P_i
\]

The number of neurons in the output layer is equal to the number of neurons of output variables \( k \) in the learning sample, and outputs of network are obtained by dividing these two different types of neuron outputs in the summation layer, i.e.

\[
y_j = \frac{S_{ij}}{S_D} \quad j = 1, 2, ..., k
\]

It can be seen that, when the sample is selected, the structure and connection weight of the GRNN network are completely determined, so the training process of GRNN network is much more convenient than the training process of back propagation (BP) network.

4 Particle swarm optimisation

PSO is an optimisation algorithm based on swarm intelligence theory, which is proposed by Kennedy and Eberhart [18]. In the standard PSO algorithm, each optimisation problem corresponds to a particle in the search space, which is characterised by three indexes of position, velocity, and fitness value. In the process of
searching optimal solution, the particle can adjust its position and velocity by tracking two ‘best solutions’. The first optimal solution is found by particle itself, i.e. the individual optimal solution; the second one is population optimal solution which is found by the whole population. The updating equations of each particle are as follows:

$$\begin{align}
    v_{i,k+1} &= w \times v_{i,k} + c_1 r_1 (P_{i,k} - X_{i,k}) + c_2 r_2 (P_g - X_{i,k}) \\
    X_{i,k+1} &= X_{i,k} + v_{i,k+1}
\end{align}$$

where $k$ is iteration time; $X_{i,k}$ is the position of $i$ particle after $k$ iterations; $v_{i,k}$ is the velocity of $i$ particle after $k$ iterations; $w$ is inertia weight; $c_1$ and $c_2$ are learning factors; $r$ is constraint coefficient (convergence factor), where $r_1$ and $r_2$ are random numbers in $[0,1]$; $P_{i,k}$ is optimal solution of each particle after $k$ iterations; $P_{g}$ is optimal solution of population after $k$ iteration.

5 AMPSO–GRNN prediction model

In this paper, an AMPSO algorithm is proposed in order to select the fittest smoothing factor. The smoothing factors are mapped to particles in proposed algorithm. After calculating fitness value of each particle, the inertia weight and learning factor can be adjusted dynamically. Then the mutation operation is taken on the part of particles when average distances of each particle in the population are larger than the requirement. By this method, the PSO algorithm can avoid premature convergence and find the fittest smoothing factor in theory. The flow chart of AMPSO algorithm is shown in Fig. 5. The algorithm steps are as follows:

Step 1: Initializing particle swarm parameters. Setting population number is $m$; initial learning factors are $c_1$ and $c_2$; final learning factors are $c_{1f}$ and $c_{2f}$; maximum iteration time is $T$, the current iteration is $t = 1$; dimension of solution space is $q$.

Defining that, in the search space $R^q$, initial position of $m$ particles ($s_1, s_2, \ldots, s_m$) are randomly generated and the position matrix $S(t)$ is composed by these particles; initial velocity of each particle $v_1, v_2, \ldots, v_m$ are also randomly generated and the velocity matrix $V(t)$ is composed by these particles.

Step 2: Each particle in the particle swarm is mapped to the corresponding smoothing factor in GRNN. Then each particle is trained by learning sample. The mean square error of each particle is calculated, and the fitness function is constructed according to the mean square error. The fitness function of each particle is calculated by (6), in which $\lambda$ represents mean square error.

$$f(\lambda) = \frac{1}{\sqrt{2 \pi}} \exp\left(-\frac{\lambda^2}{2}\right)$$

Step 3: Updating optimal solution of each particle $B_1$ and optimal solution of population $B_g$.

Step 4: Calculating inertia weight ($w_i$) and learning factor ($c_1, c_2$) of each particle by (7) and (8).

$$w_i = \frac{\eta \times (f_i - f_{\min})}{f_{ave} - f_{\min}}$$

where $\eta$ is a constant in $[0,1]$, and $\eta = 0.3$; $f_i$ is the fitness value of each particle after iterating; $f_{\min}$ is the minimum value of fitness of each particle after iterating; $f_{ave}$ is the average fitness value of each particle after iterating.

$$\begin{align}
    c_1 &= c_{1f} + t \times (c_{1e} - c_{1f})/T \\
    c_2 &= c_{2f} + t \times (c_{2e} - c_{2f})/T
\end{align}$$

Step 5: Updating inertia weight and learning factor of each particle, and updating the position and velocity of all particles according to (5).

Step 6: Calculating average particle distance $D(t)$ by (9). If $D(t) \leq 0.01$ or there is no obvious change in the population optimal position after 10 iteration times, the particle will be done mutation operation, and then enter Step 7, otherwise return to Step 2.

$$D(t) = \frac{1}{mL} \sum_{i=1}^{m} \sum_{j=1}^{L} \left| s_{id}(t) - P_d \right|$$

where $L$ is maximum length of search space; $s_{id}$ is the coordinate value of $i$ particle under the $d$ dimension; $P_d$ is the average coordinate value of all particles under the $d$ dimension.

Step 7: Mutation operation. Forty percent of all particles are performed mutation operations by (10). The optimal position $B_t$ of each particle is updated.

$$s_i' = s_i + 0.5 \times \sqrt{\frac{1}{2\pi}} e^{-\frac{d^2}{2\pi}}$$

where $s_i'$ is updated position of particle after mutating, $s_i$ represents original position of particle before mutating.

Step 8: Judging whether to meet maximum iteration time or accuracy requirement of convergence. If the requirement can be met, then continue to the next step, or return to Step 2.

Step 9: Getting optimal smoothing factor, and end algorithm.

6 Prediction result analysis

The daily ESDD data from January 1, 2015 to August 10, 2016 were collected by on-line monitoring equipment based on optical sensor. In this paper, 20 samples are randomly selected as test samples and the rest are training samples. The input variables of GRNN network are the previous day’s ESDD value, wind speed, precipitation, relative humidity, temperature, and air quality index, and the output variable is the ESDD value needed to be predicted. Among them, air quality index can reflect the number of suspended particulate matters. In the simulation model, the initial learning factor value $\eta$ is the same parameters, the PSO–GRNN model, this paper sets the same parameters, the AMPSO–GRNN model, this paper sets the same parameters, the AMPSO–GRNN prediction model, this paper sets its smoothing factor $s$ to be in $[0.001, 2]$. In the simulation model, the AMPSO–GRNN model, this paper sets the same parameters, the number of population number is $m = 100$, dimension number of search space is $q = 20$, the maximum iteration time is $T = 500$, the maximum velocity limit of particle is $v = 1$, and the range of smoothing factor is in $[0.001, 2]$. In the simulation model, the AMPSO–GRNN and PSO–GRNN models are all iterated for 200 iterations.

Fig. 5 Flow chart of AMPSO algorithm

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The comparison of the training processes of GRNN, PSO–GRNN, and AMPSO–GRNN models is shown in Table 1. The ARE of GRNN, PSO–GRNN, and AMPSO–GRNN models are 3.12, 2.03, and 1.71%, respectively, and the maximum relative error are 6.35, 4.89, and 3.98%, respectively, under the same accuracy target. It can be seen that the AMPSO–GRNN model has some advantages over the training error compared with GRNN and PSO–GRNN models. Therefore, using the AMPSO algorithm to solve the optimal smoothing factor of the GRNN model has a better performance. The AMPSO–GRNN model has certain superiority in searching ability and convergence precision, which can improve the shortcomings of PSO algorithm.

In order to test the prediction accuracy of these three prediction models, Tables 2 and 3 show prediction results of three kinds of neural network prediction models when predict the same data. It can be seen from Table 2 that the average relative errors of GRNN, PSO–GRNN, and AMPSO–GRNN are 3.12, 2.03, and 1.71%, respectively, and the maximum relative errors are 6.35, 4.89, and 3.98%, and the mean square errors are 1.16 × 10⁻³, 9.01 × 10⁻⁴, and 8.15 × 10⁻⁴, respectively. Prediction accuracy and stability of AMPSO–GRNN prediction model is significantly better than those of the GRNN and PSO–GRNN models. Therefore, this method provides a new method to make a scientific and feasible maintenance plan for the running transmission line. It is of great significance to arrange the scientific and reasonable maintenance plan in order to avoid pollution flashover accidents. Specific conclusions are as follows:

i. Adaptive mutation method can effectively improve searching ability of PSO algorithm. By this method, the algorithm can avoid premature convergence and the fault of falling into local optimal value.

ii. APSO algorithm can be used to select the optimal smoothing factor of GRNN model, which can effectively improve prediction performance. It can make prediction function further smoother and more accurate.

iii. In this paper, AMPSO–GRNN model shows that it has a great performance in predicting insulator ESDD. The prediction results of AMPSO–GRNN model are far more accurate and stable than GRNN and PSO–GRNN models. Therefore, this paper provides a new method to make a scientific and reasonable insulator maintenance plan and avoid pollution flashover accidents.
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| Number | Actual value, mg/cm² | GRNN Predicted value, mg/cm² | Percent error, % | PSO–GRNN Predicted value, mg/cm² | Percent error, % | AMPSO–GRNN Predicted value, mg/cm² | Percent error, % |
|--------|----------------------|------------------------------|-----------------|----------------------------------|-----------------|-----------------------------------|-----------------|
| 1      | 0.0486               | 0.04551                      | 6.36            | 0.04733                          | 2.61            | 0.04667                           | 3.97            |
| 2      | 0.0488               | 0.04655                      | 4.61            | 0.04725                          | 3.18            | 0.04758                           | 2.50            |
| 3      | 0.0495               | 0.04695                      | 5.15            | 0.04875                          | 1.52            | 0.04822                           | 2.59            |
| 4      | 0.0476               | 0.04763                      | 0.06            | 0.0465                           | 2.31            | 0.04851                           | 1.91            |
| 5      | 0.0471               | 0.04592                      | 2.51            | 0.04613                          | 2.06            | 0.04696                           | 0.30            |
| 6      | 0.0448               | 0.04511                      | 0.69            | 0.04473                          | 1.16            | 0.04604                           | 2.77            |
| 7      | 0.0464               | 0.04393                      | 5.32            | 0.04413                          | 4.89            | 0.04463                           | 3.81            |
| 8      | 0.0464               | 0.04469                      | 3.69            | 0.04531                          | 2.35            | 0.04547                           | 2.00            |
| 9      | 0.0464               | 0.04476                      | 3.53            | 0.04523                          | 2.52            | 0.04562                           | 1.68            |
| 10     | 0.0467               | 0.0452                       | 3.21            | 0.04598                          | 1.54            | 0.04599                           | 1.52            |
| 11     | 0.0467               | 0.04557                      | 2.42            | 0.04732                          | 1.33            | 0.04629                           | 0.88            |
| 12     | 0.0468               | 0.04571                      | 2.33            | 0.04786                          | 2.26            | 0.04623                           | 1.22            |
| 13     | 0.0469               | 0.04563                      | 2.71            | 0.04709                          | 0.41            | 0.04653                           | 0.79            |
| 14     | 0.0468               | 0.04548                      | 2.82            | 0.04649                          | 0.66            | 0.04639                           | 0.88            |
| 15     | 0.0464               | 0.04504                      | 2.93            | 0.04531                          | 2.35            | 0.04599                           | 0.88            |
| 16     | 0.0466               | 0.04496                      | 3.38            | 0.04557                          | 2.21            | 0.04569                           | 1.95            |
| 17     | 0.0467               | 0.04512                      | 3.38            | 0.04586                          | 1.80            | 0.04575                           | 2.03            |
| 18     | 0.0466               | 0.04588                      | 1.55            | 0.04779                          | 2.55            | 0.04657                           | 0.06            |
| 19     | 0.0464               | 0.04555                      | 1.83            | 0.04709                          | 1.49            | 0.04606                           | 0.73            |
| 20     | 0.0465               | 0.04475                      | 3.76            | 0.04541                          | 2.34            | 0.04565                           | 1.83            |

Fig. 8 Comparison of predicted values of three models

Fig. 9 Comparison of percentage errors of predicted values of three models

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