Residual life prediction of mining cables based on RBF neural network

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Abstract. The RBF (Radial basis Function) neural network forecasting model is constructed for the mine cable life prediction problem. According to the mine cable in line with the characteristics of accelerated life test, the temperature and the dielectric loss factor are chosen as the model input. In order to solve the problem that the number of training samples is too small and detection samples cannot be constructed, the dielectric loss factor and aging time in each temperature segment collected are linearly interpolated to generate a large number of simulation data as training target vectors, and the RBF neural network is established for life prediction. Then the predicted life value is compared with the design life of the cable for verification. The result confirms that the RBF neural network model can reflect the relationship between the dielectric loss factor and residual life under a certain humidity and the different levels of temperature, which has certain practical significance for the prediction of cable insulation life.

1. Introduction
After the XLPE is put into operation, the insulation will be affected by electricity, heat, machinery, humidity and other factors, and the aging phenomenon will occur. However, the underground working environment requires the cables to provide uninterrupted power supply to ensure the safety of underground personnel and the normal operation of electromechanical equipment, so the reliability of mine cables is particularly important. At present, the prediction methods include mathematical statistics and model method. In the national standard, the model method is used to predict the cable life, and the cable life estimation only considers the thermal stress, taking 50% of the material elongation retention rate as the criterion for the end of the life, which is deduced by the Arrhenius equation fitting. In literature [2], it is mentioned that the medium loss factor method is used to estimate the remaining life of XLPE cable. This literature points out that the relationship between the specific insulation strength and the loss factor is fuzzy, and establishes the remaining life equation of cable about \( \tan \delta \). Literature [3] points out that \( \tan \delta \) is an important indicator of insulation quality, so measuring \( \tan \delta \) is a sensitive and effective method to judge the insulation status of electrical equipment and cables, especially for distributed defects such as damp and aging. The value of \( \tan \delta \) is closely related to the insulation material used to make the cable under test. If \( \tan \delta \) is greater than 5%, it means that the cable is obviously aged or has faults, and should be repaired or replaced in time. Therefore, in this paper, \( \tan \delta = 5\% \) is used as the criterion for the end of cable life, and RBF neural network is used as the mathematical model to map the factors affecting the life and the
remaining life time.

2. RBF neural network model

In 1985, Powell proposed the Radial Basis Function (RBF) method of multivariate interpolation[4]. In 1988, Moody and Darken proposed a neural network structure, namely RBF neural network, which can approximate any continuous function with any accuracy[5]. The basic idea of RBF neural network is: using RBF as the "basis" of the hidden unit to constitute the hidden space, so that the input vector can be directly mapped (that is, without weight connection) to the hidden space, making the hidden layer exchange the input vector, mapping the input data of the low-dimensional mode to the high-dimensional space, making the linear inseparability problem in the low-dimensional space linearly separable in the high-dimensional space. Under the premise that the network structure used in this paper is as simple as possible (that is, the number of hidden layer units is as small as possible), the performance of the network is improved by optimizing RBF parameters. Radial basis network can find the minimum network to solve the problem within the given error target range. Radial basis network consists of two layers of neurons. The first layer is a hidden layer composed of S1 radial basis neurons, and the second layer is an output layer composed of S2 neurons. The structure of RBF neural network is shown in figure 1.

![Figure 1. Structure of RBF neural network](image)

In figure 1, \( a_i^1 \) is the i TH element of vector \( a^1 \), and \( IW_{1,1}^i \) is the i TH row vector of weight matrix \( IW^{1,1} \). R is the number of elements of the input vector. The input of label \( \| \text{dist} \| \) is input vector \( p \) and input weight matrix \( IW^{1,1} \), and the input vector produced includes \( S^i \) elements, each of which is the vector distance between the input vector \( p \) and the rows of matrix \( IW^{1,1} \). The deviation vector \( b_1 \) times \( \| \text{dist} \| \) is the product of the vector elements times the elements.

It is assumed that there are N training samples and M neurons in the input layer of RBF neural network, any of these neurons is denoted by m; There are I(1<N) neurons in the hidden layer, any neuron is represented by i, and the excitation output of the i TH hidden unit is "basis function" \( \phi(t_i) \). In this paper, the Gaussian function is selected as the radial basis function, where \( t_i = [t_{i1}, t_{i2}, \cdots, t_{im}, \cdots, t_{im}] \) (i \( = 1,2,\cdots, I \)) is the center of the basis function; The output layer has J neurons, one of which is represented by J. The synaptic weight of the hidden layer and the output layer is denoted by \( w_{ij} (i = 1,2,\cdots, N, j = 1,2,\cdots, P) \). The output unit also sets the threshold value \( \phi_0 \), by making the output of a neuron \( G_0 \) in the hidden layer constant one and the weight of the output unit connected to it \( w_{0j} (j = 1,2,\cdots, J) \).

Let the training sample set be \( X = [X_1, X_2, \cdots, X_k, \cdots, X_N] \), in which any training sample \( X_k = [x_{k1}, x_{k2}, \cdots, x_{km}, \cdots, x_{km}] \) (k \( = 1,2,\cdots, N \)), the corresponding actual output
is \( Y_k = \{y_{k1}, y_{k2}, \cdots, y_{kj}, \cdots, y_{kj} \mid k = 1, 2, \cdots, N \} \), and the expected output is \( d_k = \{d_{k1}, d_{k2}, \cdots, d_{kj}, \cdots, d_{kj} \mid k = 1, 2, \cdots, N \} \). When the network inputs the training sample \( X_k \), the actual output of the JTH output neuron of the network is

\[
y_{kj}(X_k) = w_{0j} + \sum_{i=1}^{I} w_{ij} \phi(X_k, t_i), j = 1, 2, \cdots, J
\]

(1)

When the "basis function" is a Gaussian function, it can be expressed as follows:

\[
\phi(X_k, t_i) = \exp\left(-\frac{1}{2\sigma_i^2} \sum_{m=1}^{M} (x_m - t_{im})^2 \right)
\]

(2)

Where \( t_i = [t_{i1}, t_{i2}, \cdots, t_{iM}] \) is the center of the Gaussian and \( \sigma_i \) is the variance of the Gaussian.

The RBF neural network learning algorithm needs to solve three parameters: the center of the basis function, the variance and the weight from the hidden layer to the output layer.

The specific steps of learning algorithm of RBF neural network are as follows:

1. Network initialization. I samples were randomly selected as the initial center \( t_i(0)(i = 1, 2, \cdots, I) \).
2. The input training sample set is grouped according to the nearest neighbor rule. Find out which center is closest to the random input training sample \( X_k \), namely find \( i(X_k) \) and make it satisfy:

\[
i(X_k) = \arg \min_i \|X_k - t_i(n)\|_i, i = 1, 2, \cdots, I
\]

Where \( t_i(n) \) is the i TH center of the basis function for the n TH iteration.

3. Readjust the clustering center. Adjust the center of the basis function with the following formula:

\[
t_i(n + 1) = \begin{cases} t_i(n) + \eta \left[X_i(n) - t_i(n)\right], & \text{where } i = i(X_k) \\ t_i(n), & \text{others} \end{cases}
\]

(3)

\( \eta \) is the learning step and \( 0 < \eta < 1 \).

4. Determine the variance \( \sigma_i \). The basis function of the RBF neural network is the Gaussian function, so the variance can be calculated by the following formula:

\[
\sigma_i = \sigma_2 = \cdots \sigma_I = \frac{d_{\max}}{\sqrt{2I}}
\]

(4)

\( I \) is the number of hidden elements, and \( d_{\max} \) is the maximum distance between the selected centers.

5. Calculate the weight \( w_{ij} \) between the hidden layer and the output layer.

The connection weight can be directly calculated by the least square method. The calculation formula is as follows:

\[
w_{ij} = \exp\left(\frac{I}{d_{\max}} \left\| X_k - t_i(n) \right\|^2 \right), k = 1, 2, \cdots, I; j = 1, 2, \cdots, J
\]

(5)

3. Accelerated life test of cable

Natural environment aging is a real and effective method to evaluate the cable life, but it has the disadvantage of a long test period. The accelerated aging of cables refers to a life evaluation method that shortens the test period by increasing the test stress while keeping the failure mechanism unchanged, and improves the test efficiency so as to make the reliability assessment of cables possible[6].

The test cable used in this paper is MYJV 22 8.7/15 kV 3 x 50 mm three-core XLPE (Cross Linked Polyethylene) cable for mine. According to the standard MT 818.11-2009, the maximum rated
operating temperature of cable conductor is 90°C, while the cross-linked polyethylene insulation material may change the crystal size at a temperature higher than 150°C, or even recross-link, at the same time, the working environment of downhole cables is humid, so the test temperature combined with the characteristics of conductor temperature and insulation material finally selected 110°C, 120°C, 130°C, 140°C, 150°C, the relative humidity of 95%RH for the wet and heat aging test, medium loss factor equal to 5% as the end of life.

4. Prediction of cable life by RBF neural network

Suppose the two input characteristic vectors are: temperature, medium loss factor; The characteristic vector of the output is the aging time. The data after linear interpolation is 150 groups, and the relevant data can be divided into two parts, of which 120 groups are used to train the RBF neural network established, and 30 groups are used as verification group for prediction. The results of the validation data are shown in table 1.

Verify the comparison between the real value of aging time of data set and the predicted value of RBF, as shown in figure 2.
Figure 2. Verifies the real value of aging time of data set and the predicted value of RBF

From table 1 and figure 2, it can be seen that the relative error between the real value and the predicted value of the validation group data is less than 2%, and the correlation coefficient $R^2=0.9989$. The analysis results show that the model has good performance.

When the radial basis neural network is trained with data, the hidden layer neurons that can be automatically increased in the radial basis network are selected, and the weight and threshold are adjusted and corrected through continuous loop iteration.

In the test samples, when the mean square error of aging time in each group at temperature is less than 25, the predicted results of the model are consistent with the actual situation. After repeated training of the RBF neural network established by 120 pairs of data, it is found that when the spread coefficient =24, it is more consistent with the actual value of aging time in several temperature segments, so the trained RBF neural network is preserved. Then, the aging time under normal stress is predicted, and the predicted life time is 260971h when the dielectric loss Angle factor of insulation reaches the end of its life under the condition of 90oc 95%rh. The predicted life time is 29.79a when converted into years, while the designed life of this type of cable is 30 years. The results show that the RBF neural network can predict the life of mine cable well. The mean square error after training is shown in figure 3.

Figure 3 shows that the training mean square error of RBF neural network decreases with the increase of neurons in the network. When the number of neurons in the network increased to the 17th, the training goal was reached, and the mean square error of RBF neural network was 24.3831.

Figure 3. The mean square error diagram of neural network training

5. Conclusions
This paper uses the generalization ability of RBF neural network to predict the life of mining cable, considers the influence of environmental humidity on the life time of mining cable, and uses the
medium loss factor as the criterion of the end of the life of mining cable. The results show that the
dielectric loss factor can reflect the length of service life, which is of practical significance to obtain
the remaining service life of mine cable by on-line measurement of dielectric loss factor and the
historical use of cable. The error analysis and correlation coefficient show that the RBF neural network
can effectively predict the cable life, and the temperature has a great influence on the cable life. For
example, the trained RBF neural network predicts that the life of mine cables at 90℃ and 110℃ is
260971h and 51232h respectively. At present, only the life of environmental relative humidity of
95%RH has been studied in this paper. The future emphasis is to study the life of mine cables under
different humidity and to predict the life of mine cables through online collection of medium loss
factor.

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