Research on electrical life Trace prediction of contact based on SG-BP algorithm

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Abstract. In order to prevent electrical fire in low-voltage distribution system, it is a very effective measure to predict the electrical life of various low-voltage electrical appliances running on the line. At present, it is difficult to predict the residual electrical life of AC contactors. How to establish a reasonable and reliable prediction model for the residual electrical life of AC contactors is the key to the electrical life test and characteristic research of AC contactors. In this paper, Savitzky-Golay convolution smoothing algorithm is combined with BP neural network algorithm, and the remaining electrical life prediction model of contact is established by taking the arcing time, arcing energy and contact opening phase angle as the input parameters of the prediction model. The test results show that the average relative error of BP residual electrical life prediction model is less than 4%, and the maximum relative error is less than 10%. Combined with Savitzky-Golay convolution smoothing algorithm, SG-BP residual electrical life prediction model has average relative error less than 3% and maximum relative error less than 8%, which improves the prediction accuracy of residual electrical life, and lays a good foundation for making safe and reliable judgment by making better use of electrical life trace data.

1. Introduction
When the switch is on and off, the phenomena of liquid metal bridge, arc and spark discharge appear between the contacts due to the action of heat and electricity. The accumulation of arc will cause the wear of contact materials. With the increase of the operation times of electrical life test, the amount of wear will increase with a certain law. When it reaches a certain failure threshold, the contact will fail, and even cause serious damage such as electrical fire. Therefore, in order to prevent electrical fire in low-voltage distribution system, it is a very effective measure to predict the life of various low-voltage electrical appliances running on the line. The life monitoring of low-voltage electrical apparatus includes the monitoring of mechanical life and electrical life. Because the mechanical life is generally much longer than the electrical life, and the electrical life is more direct than the monitoring means of mechanical life, the real-time prediction of electrical life is more necessary and feasible. Although surface roughness, loss quality, effective contact distance and spectrum analysis can be used to reflect the contact erosion process, it is difficult to realize online measurement and analysis of these methods [1-3]. Therefore, electrical traces such as pull-in time, overtravel time, breaking time, arcing time, contact resistance, arcing energy and breaking current are commonly used to predict the residual electrical life of contacts by establishing a prediction model. Different research objects or different
prediction methods will have a greater impact on the prediction results. At present, mathematical statistics, fuzzy clustering and neural network are the main forecasting methods. It is difficult to predict the residual electrical life of AC contactor. Therefore, how to establish a reasonable and reliable prediction model for the residual electrical life of AC contactor is the key to the electrical life test and characteristic research of AC contactor, and it is also one of the important research directions for the reliability of AC contactor at home and abroad in recent years. In this paper, Savitzky-Golay convolution smoothing algorithm is combined with BP neural network algorithm, and the remaining electrical life prediction model of contact is established by taking arcing time, arcing energy and contact opening phase angle as the input parameters of the prediction model, which improves the accuracy of electrical life trace prediction. In order to make better use of electrical life trace data to make a safe and reliable judgment, and lay a good foundation to prevent the occurrence of electrical fire.

2. SG-BP algorithm

2.1. BP neural network algorithm
In 1986, the scientific research group led by Rumelhart and McClelland first put forward the concept of BP (back propagation) neural network, which is a kind of multilayer feedforward network trained by error back propagation algorithm [4-6]. The structure of BP neural network is shown in Figure 1.

![BP neural network structure diagram](image)

In Figure 1: $x_j$ refers to the input of the first node of the input layer, $j=1,\ldots,M$; $w_{ij}$ refers to the weight between $i$ node of the hidden layer and $j$ node of the input layer; $\theta_i$ refers to the threshold of $i$ node of the hidden layer; $\phi(x)$ refers to the incentive function of the hidden layer; $w_{ki}$ refers to the weight between $k$ node of the output layer and $i$ node of the hidden layer, $i=1,\ldots,q$; $a_k$ refers to the threshold value of the output layer node $k$, $k=1,\ldots,L$; $\psi(x)$ refers to the excitation function of the output layer; $O_k$ refers to the output of $k$ node of the output layer.

The learning process of BP is composed of forward propagation and backward propagation.

2.2. SG convolution smoothing algorithm
Savitzky-Golay filtering (SG) is a filtering method using local polynomial least square fitting in time domain. It can filter out noise while keeping the shape and width of waveform signal unchanged, so it is widely used in data stream smoothing and denoising [7-8].
When the moving smoothing algorithm is used to filter the waveform signal, the high-frequency component of the waveform signal is smoothed out, and only the low-frequency component of the waveform signal is fitted. Therefore, if the noise signal is at the high frequency component, the noise will be removed after filtering. If the noise signal is at the low frequency component, the noise signal will be left after filtering. For data  , the moving smoothing method is used for filtering, and the principle is shown in Figure 2.

![Figure 2: Schematic diagram of moving smoothing algorithm filtering.](image)

The effect of smoothing filter varies with the width of the selected window, the smoothing process can be expressed as follows:

\[
x_{k,\text{smooth}} = \bar{x}_k = \frac{1}{2w+1} \sum_{i=-w}^{w} x_{k+i}
\]  

\( (1) \)

Savitzky-Golay convolutional smoothing algorithm is an optimization improvement of mobile smoothing algorithm, the formula is as follows:

\[
x_{k,\text{smooth}} = \bar{x}_k = \frac{1}{H} \sum_{i=-w}^{w} x_{k+i} h_i
\]  

\( (2) \)

Each measured value is multiplied by the smoothing coefficient  , to minimize the influence of the smoothing denoising algorithm on the useful information of the waveform. The shortcomings of the smoothing denoising algorithm can be improved by using the least square principle and polynomial fitting.

The key of Savitzky-Golay convolution smoothing algorithm is how to find the matrix operator. Assuming the width of the filter window is  , each measurement point is expressed as  , the data points in the window are fitted by  degree polynomial, as follows:

\[
y = a_0 + a_1 x + a_2 x^2 + \ldots + a_{k-1} x^{k-1}
\]  

\( (3) \)

We can get  such equations to form a system of  ary linear equations. When  is selected, the equations will have solutions, and the fitting parameter  is obtained by the least square method. So there are:
It is described by matrix as follows:

\[
\begin{pmatrix}
1 & -m & \cdots & (-m)^{k-1} \\
1 & -m+1 & \cdots & (-m+1)^{k-1} \\
\vdots & \vdots & \ddots & \vdots \\
1 & m & \cdots & (m)^{k-1}
\end{pmatrix}
\begin{pmatrix}
a_0 \\
a_1 \\
\vdots \\
a_{k-1} \\
e_m
\end{pmatrix}
\]

(4)

\[
Y_{(2m+1)\times1} = X_{(2m+1)\times k} \cdot A_{k\times1} + E_{(2m+1)\times1}
\]

(5)

The least square solution \( \hat{A} \) of \( A \) is:

\[
\hat{A} = \left( X^T \cdot X \right)^{-1} \cdot X^T \cdot Y
\]

(6)

The model prediction value or filtering value \( \hat{Y} \) of \( Y \) is:

\[
\hat{Y} = X \cdot \hat{A} = X \cdot \left( X^T \cdot X \right)^{-1} \cdot X^T \cdot Y = B \cdot Y
\]

(7)

Savitzky-Golay convolution smoothing algorithm is used to denoise the test data of A-phase contact arcing time, arcing energy and contact opening phase angle of AC contactor prototype. The comparison before and after denoising is shown in Figure 3. It can be seen that the SG convolution smoothing algorithm can effectively remove the noise signal in the original waveform, and the local mutation characteristics in the waveform are preserved, so that the shape, size and variation law of the waveform are not affected.
2.3. **SG-BP algorithm**

In this paper, Savitzky-Golay convolution smoothing algorithm and BP neural network algorithm are combined to create a contact residual electrical life prediction model based on SG-BP. After filtering and preprocessing the training samples of neural network by SG, BP neural network training is carried out. The flow of the algorithm is shown in Figure 4 below. Based on the algorithm, a single parameter prediction model of contact residual electrical life is established by using MATLAB software, and the prediction results are compared with BP neural network prediction model.

![SG-BP algorithm flow chart](image)

**Figure 4.** SG-BP algorithm flow chart.
When the input sample is used to train the prediction model, if the input of eigenvectors is too little, the remaining electrical life of the contactor cannot be accurately predicted; if the input of eigenvectors is too much, some irrelevant eigenvectors may lead to poor convergence of the network. In this paper, the arcing time, arcing energy, contact opening phase angle are selected as the inputs of SG-BP residual electrical life prediction model, so the input nodes of the network are 1, 2 and 3 respectively.

The output vector is the target of prediction, and the remaining electrical life of contactor contact and the number of electrical life test operations are a corresponding time series. Therefore, this paper selects the remaining electrical life of contact as the output vector, and the number of network output layer nodes is 1.

Input sample preprocessing. The data samples of 150 groups of A-phase contacts of the prototype in the first 15000 electrical life tests are collected. Because the actual electrical life of the prototype is 125296 times, the remaining electrical life of each contact corresponding to the data sample is 125296, 125196, 125096 ...110396. The 150 data samples were randomly divided into two groups, the first group of 140 samples were used to train SG-BP neural network, the second group of 10 samples were used to predict SG-BP neural network. At the same time, the data samples are normalized, and the mapminmax function is used to normalize the data to [-1, 1], so as to avoid the influence caused by the order of magnitude difference of each parameter.

3. SG-BP residual power life prediction model

3.1. Network structure design

Literature [9-10] has proved that BP neural network with single hidden layer can approach nonlinear physical objects with any precision. Although increasing the number of network layers can reduce the prediction error, it also makes the network more complex and more training time. The increase of the number of hidden layer neurons in the single hidden layer network can also improve the prediction accuracy, and the training is easier to achieve, so this paper chooses the single hidden layer network structure.

The selection of the number of hidden layer nodes has a certain relationship with the number of training samples, the complexity of data rules in training samples, and the size of training sample noise. The number of hidden layer nodes can be selected according to the empirical formula:

$$m = a + \sqrt{n + 1}, m \geq \sqrt{n}$$

Where, $n$ refers to the number of input layer nodes, $m$ refers to the number of hidden layer nodes, $l$ refers to the number of output layer nodes, $a$ can be considered as a constant between (1 ~ 10).

For the single parameter prediction model, $n=m=1$, then $3 \leq m \leq 11$. Select the same sample, train the SG-BP neural network with different number of hidden layer neurons, compare the convergence speed, convergence curve and network error in the training process, and get the relationship curve between the training value and expected value of transfer function. The training results of hidden layer 3, 6, 9 and 11 are shown in Figure 5.
Figure 5. (a) (b) (c) (d) Training results of hidden layer of neural network.

It can be seen from Figure 5 that the convergence speed of training with 1-9-1 network structure is relatively fast, the number of training steps is less, the training curve is relatively smooth, and the training error is also small.

Generally, S-type logarithmic function (logsig), S-type tangent function (Tansig) and pure linear function (purelin) are selected as transfer functions, which are differentiable monotone increasing functions. In this paper, Tansig is used as the transfer function of the hidden layer and purelin as the transfer function of the output layer.

The training parameters include initial weight, learning rate and expected error. The initial weights directly affect the training time of neural network, and whether the training can converge or not. Generally, they are random numbers between (-1, 1). Each training will change randomly, so the initial value is fixed by using the setdemorandstream (pi) command. Generally, a small expected error is set for network training. If the error does not change with the increase of training times, this error is selected as the expected error. In this paper, the expected target is set as 0.001. The learning rate reflects the speed of network learning and determines the range of weight modification. Generally, it tries repeatedly between (0.01~0.08). The smaller the learning rate is, the more stable the system is. The learning rate of this paper is set as 0.01.

By training the same sample with different algorithms, the number of training steps and average relative error of each algorithm are obtained, as shown in Table 1. It can be seen that the training steps and average relative error of trainbfg and trainlm are better, but from their training curves, we can see
that trainbfg has less training steps than trainlm, and the convergence curve is more stable, so trainbfg is selected as the training function.

Table 1. Training results of different algorithms.

| Number | Training algorithm and function | Training steps (steps) | Average relative error (%) |
|--------|--------------------------------|------------------------|---------------------------|
| 1      | traingd                        | 1270                   | 3.71                      |
| 2      | traingdm                       | 1260                   | 3.65                      |
| 3      | traingda                       | 94                     | 3.63                      |
| 4      | traingdx                       | 46                     | 4.71                      |
| 5      | trainlm                        | 14                     | 3.35                      |
| 6      | trainbfg                       | 13                     | 3.59                      |
| 7      | trainrp                        | 17                     | 3.24                      |

3.2. Residual electrical life prediction model of SG-BP contact

Two groups of test data samples are selected after the pretreatment of the prototype. Each sample contains the operation times, arcing time, arcing energy, contact opening phase angle, residual electrical life and other data of phase a contact electrical life test. The first group of 140 samples are training samples, and the second group of 10 samples are test samples. The prediction effect is compared with the actual situation.

Taking the arcing time, arcing energy and contact opening phase angle as the input and the remaining electrical life of contact as the output, the single parameter SG-BP contact remaining electrical life prediction model is realized by using MATLAB software. The trained SG-BP neural network is used to predict the output of 10 test samples, and the simple BP neural network is used to predict the output. The output and expected relative error of the prediction model are obtained respectively, as shown in Figure 6, Figure 7 and Figure 8. For the convenience of analysis, the prediction error is counted, as shown in Table 2.

![Figure 6](image-url)  
(a) Prediction results.  
(b) Prediction error.  

Figure 6. (a) (b) Prediction results of arcing time as input variable.
Figure 7. Prediction results of arcing energy as input variable.

Figure 8. Prediction results of contact opening phase angle as input variable.

Table 2. Prediction error of different life prediction models.

| Test prototype input parameter | Comparison of relative error of neural network prediction (take absolute value) |  |
|-------------------------------|--------------------------------------------------------------------------------|---|
|                               | Maximum relative error (%) | Minimum relative error (%) | Average relative error (%) | BP | SG-BP | BP | SG-BP | BP | SG-BP |
| Arcing time                   | 6.53                        | 0.05                        | 3.33                        | 4.94 | 0.55 | 2.96 |
| Arcing energy                 | 9.51                        | 0.77                        | 3.77                        | 7.04 | 0.18 | 2.87 |
| Opening phase angle           | 7.59                        | 0.18                        | 3.79                        | 4.88 | 0.94 | 2.69 |

It can be seen that when the arcing time, arcing energy and contact opening phase angle are taken as input variables, the average relative error of BP residual electrical life prediction model is less than 4%, and the maximum relative error is less than 10%. The average relative error of SG-BP residual power life prediction model based on Savitzky-Golay convolution smoothing algorithm is less than 3%, and
the maximum relative error is less than 8%, which improves the prediction accuracy of residual power life. Therefore, the prediction model of SG-BP contact residual electrical life is better than that of BP neural network.

4. Conclusions

(1) By combining Savitzky-Golay convolution smoothing algorithm with BP neural network algorithm, the residual electrical life prediction model of contact is established with arcing time, arcing energy and contact opening phase angle as input parameters of the prediction model;

(2) The test results show that the average relative error of SG-BP residual power life prediction model is less than 3%, and the maximum relative error is less than 8%, which improves the prediction accuracy of residual power life. In order to make better use of electrical life trace data to make a safe and reliable judgment, and lay a good foundation to prevent the occurrence of electrical fire.

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