An arc contacts life assessment method based on dynamic resistance measurement and bp neural network

Bangfa Chen¹, Xianxi Chen¹, Muxin Diao², Guangyu Xiao², Jing Yan² and Zhenxing Wang²

¹Foshan Power Bureau, Guangdong Power Gird, Foshan, China
²State Key Laboratory of Electrical Insulation and Power Equipment, Xi’an Jiaotong University, Xi’an, China

bangfavvchen@163.com, 799408401@qq.com, diaomx@stu.xjtu.edu.cn, xgy1996@stu.xjtu.edu.cn, yanjing@mail.xjtu.edu.cn, zxwang@xjtu.edu.cn

Abstract. Arc contacts ablation of high voltage SF₆ circuit breaker will cause potential problems for safe operation of the grid. In view of the difficulty of predicting arc contacts life by existing methods, an arc contacts life assessment method based on dynamic contact resistance and BP neural network is proposed. The dynamic contact resistance-travel curve is obtained from the high-current ablation experiments, from which the data characterizing the arc contacts state is extracted as samples to train the neural model. The model is optimized by k-fold cross-validation method, which is finally validated by experimental results. The results show that the arc contacts life prediction value agrees well with the experimental value, which means that the BP neural network can effectively predict the arc contacts life and provide a basis for decision making for arc contacts overhaul and replacement.

1. Introduction
High-voltage circuit breaker is the most important protection equipment in the power system, featuring large breaking capacity as well as frequent operation, etc. In the course of power system operation, due to the frequent fluctuation of the load in the grid, it is required to frequently switch capacitor banks to compensate for reactive power with the purpose of improving the power factor of the grid. The frequent switching operation leads to serious ablation of SF₆ circuit breaker contacts, causing hidden danger to the safe operation of the ultra-high voltage grid.

The main contacts of high voltage SF₆ circuit breaker mainly bear the role of current flow, and the arc contacts bear the function of arc extinguishing. After the circuit breaker is closed several times, the moving and static arc contacts undergo different degrees of ablation, resulting in increased contact resistance and surface roughness. Therefore, the arc contacts status of the high-voltage circuit breaker interrupter chamber is the key factor determining the life of the circuit breaker. Statistics show that the breaking short-circuit current failures of SF₆ circuit breaker caused by severe ablation of arc contacts account for about 10% of the total faults [1], so it is particularly important to detect the arc contacts status of SF₆ circuit breaker timely and replace them according to the test results.

Research on circuit breaker fault detection mainly focuses on mechanical faults. The diagnostic signals used mainly include vibration signals [2, 3] and current signals of opening and closing coils [4-6]. However, existing methods for fault detection of arc contacts within the interrupter are less common. The conventional method of measuring the static contact resistance of circuit breaker can only reflect the ablation state of main contacts, but not the ablation state of arc contacts. Dynamic
resistance measurement (DRM) is to measure the dynamic contact resistance of the moving and static contacts during the opening or closing process of a high-voltage circuit breaker. The measured dynamic contact resistance curve contains a wealth of arc contacts status information, which can be used to assess arc contacts state. M. Landry [7, 8] and others proposed to use the dynamic contact resistance-travel curve during the opening process to assess the state of arc contacts, however the existing assessment method based on dynamic contact resistance-travel curve is lack of a unified criterion, and there are problems of incomplete evaluation parameters, inadequate evaluation methods, and inaccurate evaluation status.

In order to solve the above problems, this paper proposes a method for assessing the life of SF₆ circuit breaker arc contacts based on BP neural network by extracting assessment parameters from the dynamic contact resistance-travel curve.

2. Arc contacts life assessment method
Since the dynamic contact resistance curve of the arc contacts in the closing process of circuit breaker is susceptible to a variety of factors such as vibration, noise and speed, the curve is relatively stable only during the opening process of the circuit breaker [9]. Therefore, the dynamic contact resistance-travel curve of arc contacts during opening process is selected as the data for arc contacts life assessment.

- **Average dynamic contact resistance of arc contacts** R: A typical dynamic contact resistance-travel curve is shown in Figure 1. Based on the experimental data, we believe that the moving and static arc contacts are more stable in connection with a contact travel of 0 to 35 mm, so the dynamic contact resistance data of this part was chosen for calculation.

- **Standard deviation of the dynamic contact resistance of arc contacts** σ: The standard deviation of dynamic contact resistance of stable connection part is calculated. The standard deviation reflects the degree of dispersion of contact resistance. The smaller the dispersion of contact resistance, the better connection of moving and static arc contacts, indicating that the ablation is slight. The greater the dispersion of contact resistance, the more serious ablation of moving and static arc contacts. Therefore, the standard deviation of dynamic contact resistance is a good indicator of the degree of arc contacts ablation.

- **Circuit Breaker Closing Current** I: The current carried by the high-voltage circuit breaker when switching the capacitor bank will severely ablate the arc contacts, resulting in an increase in the contact resistance and damage to contact surface structure. Generally speaking, the greater the current, the more severe the ablation of arc contacts, and vice versa.

- **Maximum contact travel of arc contacts** D: As the static arc contact is ablated, it becomes progressively shorter in length and more sharp at the tip. This will lead directly to a reduction in contact travel. The sharpened tip of the static arc contact is easy to cause the connection to be weak, resulting in large fluctuations in the contact resistance curve. So the contact travel is an important parameter to reflect the degree of arc contacts ablation.

![Figure 1. Typical dynamic contact resistance-travel curve for arc contacts.](image-url)
Based on the above dynamic contact resistance data, this paper proposes an SF$_6$ circuit breaker arc contacts life assessment method based on BP neural network. This method is used to assess the remaining life of arc contacts and quantify the remaining life as the number of remaining switchable closures $n$ of the capacitor bank for a circuit breaker switching at a given current, as shown in Figure 2.

**Figure 2.** SF$_6$ circuit breaker arc contacts life assessment method

In order to obtain samples for training BP neural network, six pairs of contacts were subjected to closing ablation experiments at different currents (10, 15, 20, 25, 30, and 35 kA), with five dynamic contact resistance curves measured after every 25 closing ablation experiments. When the average of the five arc contacts dynamic contact resistance is greater than 450μΩ, the remaining life of the arc contacts is considered to be 0, that is, the arc contacts erosion is quite serious at this time, and the circuit breaker is considered to be in an abnormal operating state. A total of 221 sets of data were obtained in the experiment, some of the experimental data are shown in Table 1.

**Table 1.** Experimental data on the dynamic contact resistance of arc contacts.

| Sample number | $R/μΩ$ | $σ$ | $I/kA$ | $D/mm$ | $n$/times |
|---------------|--------|-----|--------|--------|-----------|
| 1             | 107    | 43  | 10     | 41     | 2838      |
| 2             | 86     | 57  | 10     | 41     | 2822      |
| 3             | 101    | 83  | 10     | 41.8   | 2805      |
| 4             | 81     | 65  | 10     | 39.5   | 2788      |
| 5             | 120    | 87  | 10     | 39.5   | 2772      |
| 6             | 148    | 34  | 20     | 40.47  | 283       |
| 7             | 143    | 33  | 20     | 39.5   | 266       |
| 8             | 135    | 62  | 20     | 39.5   | 250       |
| 9             | 78     | 33  | 30     | 39.6   | 177       |
| 10            | 130    | 65  | 30     | 39.73  | 160       |

In order to avoid saturating the neuron output due to the large absolute value of the net input and then causing the weight adjustment to enter the flat region of the error surface, the original training samples need to be normalized and the input and output data need to be transformed to the values in the [-1,1] interval.

\[
x_{\text{mid}} = \frac{x_{\text{max}} + x_{\text{min}}}{2}
\]

\[
x_{io} = \frac{x_i - x_{\text{mid}}}{0.5(x_{\text{max}} - x_{\text{min}})}
\]
Where $x_{\text{mid}}$ is the median value of the training sample data, $x_{\text{min}}$ is the minimum value of the original sample data, $x_{\text{max}}$ is the maximum value of the original sample data, $x_{io}$ is the $i$-th feature parameter after normalization, $x_i$ represents raw sample data.

Some of the normalized experimental data are shown in Table 2.

### Table 2. Some of the normalized experimental data.

| Sample number | $R_0$  | $\sigma_0$ | $I_0$  | $D_0$  | $n_0$  |
|---------------|--------|------------|--------|--------|--------|
| 1             | -0.625 | -0.627     | -1     | 0.467  | 1      |
| 2             | -0.896 | -0.111     | -1     | 0.467  | 0.988  |
| 3             | -0.703 | 0.852      | -1     | 1      | 0.976  |
| 4             | -0.961 | 0.185      | -1     | -0.533 | 0.963  |
| 5             | -0.458 | 1          | -1     | -0.533 | 0.952  |
| 6             | -0.097 | -0.963     | -0.2   | -0.62  | -0.868 |
| 7             | -0.161 | -1         | -0.2   | 0.113  | -0.881 |
| 8             | -0.265 | 0.074      | -0.2   | -0.533 | -0.893 |
| 9             | -1     | 0.77       | 0.6    | -1     | -0.95  |
| 10            | -0.33  | -1         | 0.6    | -0.6   | -0.96  |
| 11            | 0.73   | -0.704     | 0.6    | -0.833 | -0.97  |

### 3. Neural network modelling

#### 3.1. BP neural network

Inspired by biology, an artificial neural network consists of a series of simple units tightly connected to each other. It simulates the operation of neurons in the human brain and builds a simplified mathematical model of the interaction process of the input complex information. The basic idea of the BP algorithm is that the learning process is divided into two processes: forward propagation and backward propagation. In forward propagation, an input signal is passed from the input layer to the output layer after processing at each hidden layer. If the actual result of the output layer does not match the expected result, the output error is transmitted back to the input layer through the hidden layer. The error is then apportioned to all units in each layer to obtain the error signal for each layer unit. This error signal is the basis for correcting the weights of each unit. The most common application of single hidden layer network using the BP algorithm is shown in Figure 3. It contains an input layer, an output layer and a hidden layer. The $x_i$ and $y_i$ are the input and output, respectively [10, 11].
Figure 3. Three-layer BP neural network.

There are five input parameters to the BP neural network and the physical meaning of each parameter is shown in Table 3. In this paper, we will predict the remaining life of the arc contacts given the mean dynamic contact resistance, the standard deviation of dynamic contact resistance, the magnitude of the closing current and the maximum contact travel of the arc contacts. Therefore the number of input layer nodes of the constructed BP neural network is 4 and the number of output layer nodes is 1. A common method to determine the optimal number of hidden nodes is trial-and-error, that is, a training network with fewer hidden nodes will be set up first, and then gradually increase the number of hidden nodes. The number of hidden nodes corresponding to the smallest network error is taken for the condition of the same training sample. When using this method, the empirical formula for estimating hidden nodes is:

$$m = \sqrt{n + l + a}$$

(3)

where $m$ is the number of hidden layer nodes, $n$ is the number of input layer nodes, $l$ is the number of output layer nodes, and $a$ is a constant between 1 and 10. Therefore, the number of hidden layer nodes can be taken from 4 to 13. It has been verified that the number of hidden layer nodes in this model takes 8.

In neural network, a neuron processes the input information using the Activation Transfer Function, then gives the output of the neuron. The sigmoid function is often used for the activation transfer function of a neural network, which is expressed as follows:

$$h(x) = \frac{1}{1 + e^{-x}}$$

(4)

Table 3. The input of BP neural network.

| No | Input parameter | Physical significance |
|----|-----------------|-----------------------|
| 1  | $R$             | Average dynamic contact resistance of arc contacts |
| 2  | $\sigma$       | Standard deviation of dynamic contact resistance of arc contacts |
| 3  | $I$            | The size of closing current |
| 4  | $D$            | Maximum contact travel of arc contacts |
| 5  | $n$            | Number of remaining closures |

The overall flow diagram of the BP algorithm is shown in Figure 4.
3.2. Model optimization
In order to improve the accuracy of the arc contacts life assessment model, this paper adopts k-fold cross-validation as an optimization tool. In the process of training the model, the problem of overfitting often occurs, that is, the model can match the training data well, but large errors occur in predicting the test dataset, resulting in poor accuracy of model evaluation results. K-fold cross-validation can make full use of the existing dataset, it divides the raw data into k groups, from which a set of samples is selected as the test dataset, and the remaining k-1 groups are used as the training dataset to train the model. After k cycles, each dataset has been verified as a single test set, so the k cross-validation errors corresponding to the k models are obtained. The training and test sets corresponding to the smallest cross-validation errors are selected to retrain the final neural network model, which can achieve the best training effect and minimize the overfitting problem.

3.3. Model training and evaluation
165 groups of normalized data were selected as the training sample for this model, and the sample data were entered into the model. The learning rate determines the amount of weight change produced in each training cycle, if the learning rate is chosen too large, it will lead to system instability; A learning rate that is too low, while beneficial for finding the minimum error, can result in too long a training time, slowing convergence. The learning rate is generally chosen between 0.01 and 1. In this paper, the learning rate is chosen to be 0.035. The training allowance error ε is set to be 0.00065 and the maximum number of iterations is 60,000. The training error curve of BP neural network is shown in Figure 5. The training error reaches the preset value when the number of training times is about to reach 60,000.
The predicted effect is evaluated using the mean absolute percentage error (MAPE), calculated as follows:

$$\text{MAPE}(x, y) = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - x_i}{x_i} \right| \times 100\% \quad (5)$$

where $N$ is the data set dimension, $y_i$ is the predicted value of arc contacts life, and $x_i$ is the experimental value of arc contacts life.

4. Neural network modelling
A total of 56 groups of test samples are selected for the prediction of arc contacts lifetime using the trained neural network model. Substituting the predicted remaining life before and after optimization into Eq. (5) yields MAPE values of 13.1% and 8.9%, respectively. The predicted results under some of these currents are shown in Table 4.

Table 4. The input of BP neural network.

| Sample number | $I$/kA | Actual value /times | Predictive value /times | Predictive value /times |
|---------------|--------|---------------------|-------------------------|-------------------------|
|               |        |                     | (Before optimization)   | (After optimization)    |
| 1             | 15     | 1867                | 2027                    | 1986                    |
| 2             | 15     | 1770                | 1564                    | 1643                    |
| 3             | 20     | 216                 | 164                     | 183                     |
| 4             | 20     | 233                 | 238                     | 236                     |
| 5             | 25     | 230                 | 185                     | 196                     |

5. Conclusion
The opening part of dynamic contact resistance-travel curve contains important information that characterizes the state of the arc contacts. By extracting the curve information, a SF$_6$ circuit breaker...
arc contacts life assessment method based on BP neural network is proposed. The model has higher calculation efficiency and better generalization ability.

The model quantifies the remaining life as the number of remaining switchable closures \( n \) of the capacitor bank for a circuit breaker switching at a given current. The mean absolute percentage error of the optimized model is 8.9%, which provides a reliable reference for field engineers to replace the arc contacts.

Due to the limited experimental data, the output error of the model is still large, and the performance needs to be further improved. When more experimental data are obtained for training and optimization, the prediction accuracy of the arc contacts life will be further improved.

6. Reference

[1] Lindquist T M, Bertling L, Eriksson R, “Circuit breaker failure data and reliability modelling,” Generation Transmission & Distribution IET, Vol.2, No.6, pp.813-820, 2008

[2] Sun L J, Hu X G and Ji Y C, “Fault Diagnosis for High Voltage Circuit Breakers With Improved Characteristic Entropy of Wavelet Packet,” Proceedings of The Chinese Society for Electrical Engineering, Vol.27, No.12, pp.103-108, 2007

[3] Huang J, Hu X G and Gong Y N, “Machinery Fault Diagnosis of High Voltage Circuit Breaker Based on Empirical Mode Decomposition,” Proceedings of The Chinese Society for Electrical Engineering, Vol.31, No.12, pp.108-113, 2011

[4] Razi-Kazemi A, Vakilian M, Niayesh K and Lehtonen M, “Circuit-Breaker Automated Failure Tracking Based on Coil Current Signature,” IEEE Transactions on Power Delivery, Vol.29, No.1, pp.283-290, 2014

[5] Zaro F R, Al-Takrouni S O and Abido M A, “Efficient On-Line Detection Scheme of Voltage Events Using Quadrature Method,” International Journal of Electrical and Electronic Engineering & Telecommunications, Vol.8, No.2, pp.95-102, 2019

[6] Vadivelu K R and Marutheswar G V, “Maximum Loadability Estimation for Weak Bus Identification Using Fast Voltage Stability Index in a Power Transmission System By Real-Time Approach,” International Journal of Electrical and Electronic Engineering & Telecommunications, Vol.3, No.1, pp.84-91, 2014

[7] Landry M, Mercier A, Ouellet G, Rajotte C, Caron J, Roy M and Brikci F, “A New Measurement Method of the Dynamic Contact Resistance of HV Circuit Breakers,” 2005/2006 IEEE/PES Transmission and Distribution Conference and Exhibition, pp. 1002-1009, 2006

[8] Landry M, Turcotte O and Brikci F, “A Complete Strategy for Conducting Dynamic Contact Resistance Measurements on HV Circuit Breakers,” IEEE Transactions on Power Delivery, vol.23, no.2, pp.710-716, 2008

[9] Liu Y, Zhang G, Qin H, Song Z, Wang J and Yang J, “Study of DRM During Closing Period of High Voltage Circuit Breaker,” IEEE Holm Conference on Electrical Contacts, pp. 95-98, 2018

Acknowledgments

This work was supported by the science and technology project of China Southern Power Grid Company (GDKJXM20184109).