Electromagnetic Waveform Identification of Electric Spark Based on BP Neural Network

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Abstract. Electromagnetic wave of electrical spark is a potential cause to electrical equipment failure. This research focused on identifying and comparative analyzing the different types of electromagnetic waveform generated by electrical equipment failure based on BP neural networks. After analyzing and extracting the features the electromagnetic waveform, BP neural network was chosen to build and train model because of fewer actual samples. The collected standard electromagnetic waveforms were used as the input of the train model, so that the nonlinear mapping between the input electromagnetic wave characteristics and the output electromagnetic wave types of the network can be maximally simulated. The model accuracy was improved by adjusting training parameters after analyzing the results. Then adjusted models were used to identify the types of electromagnetic waveforms. The result shows that the identification of electrical spark electromagnetic waveform based on BP neural network is effective and feasible.

1. Introduction
Under the influence of the power frequency electric field, the electric spark is a phenomenon of breakdown discharge when strong electric field ionizes the gas in the contact gap because of a momentary strong electric field or quick close and disconnection, together with a series of light, heat and other phenomena, which results the resistance cannot continue to maintain the insulation property. Electric spark exhibits a wide frequency band distribution over the entire frequency band of electromagnetic waves shown in the recent studies.

2. The Extraction of Electromagnetic Characteristics and the Model Establishment of the Electric Spark waveforms
Spark discharges generate electromagnetic pulses of transient, high frequency, short rise time and duration compared with electrostatic and lightning spark generation mechanisms. The difference among them is the electric spark does not have the electrostatic field generated by the initial accumulated electrostatic charge, but the electromagnetic pulse generated by the discharge is the same. The electric spark pulse electromagnetic field is the electromagnetic field generated by the discharge transient current [1].

2.1. Electromagnetic Characteristics Extraction of the Electric Spark
When the distance between the contact closure electrodes gradually decreases or a strong electric field occurs, the current density gradually increases and produces high temperature ionization, then contact and electrode gas will be punctured. The moment of touch contact or electric field reaching
maximum leads to the discharge current reaches a peak, and then current decreases with exponential to zero [2]. So, the relationship between the voltage across the capacitor and the breakdown voltage can be described as follow:

$$u_c = U_c e^{-\delta} \left( \cos \omega t + \frac{\delta}{\omega} \sin \omega t \right) + \frac{u_d e^{-\delta}}{t - \frac{T_{RC}}{T_{LR}}} \cos \frac{2(2n-1)\omega t}{2n-1}$$  \hspace{1cm} (1)

The electric current passed through electric spark can be described as follow:

$$I = C_o u_c = \frac{U_c e^{-\delta}}{w} \sin \omega t - \frac{C_o u_d e^{-\delta}}{T_{LR} - T_{RC}} \cos \frac{2(2n-1)\omega t}{2n-1}$$  \hspace{1cm} (2)

Where $T_{LR} = \frac{2L}{R}$, $w = \sqrt{\frac{T_{LR} - T_{RC}}{T_{LR}}}$, $\delta = \frac{R}{2L} = \frac{1}{T_{ix}}$. The $u_c$ is voltage of the capacitor, $C_o$ is the value of the capacitor, $T_{LR}$ and $T_{RC}$ is the delay time of inductor and capacitor.

The parameters of the electrical spark obtained by above formulas mainly include discharge voltage, discharge current, frequency, amplitude, energy, and wavelength and rise time. Different types of discharge sparks have great differences in the four parameters [3], namely, amplitude, frequency, rise time, and discharge current. Therefore, the amplitude, frequency, rise time, discharge current, and discharge voltage are selected as the parameters of the electromagnetic wave, which are the object of the subsequent analysis.

2.2. Establishment of Electric Spark Magnetic Field Model Based on BP Neural Network

The sample data for electrical spark electromagnetic wave identification include training samples, desired outputs, and spark samples. The known spark sample data [4] were determined as neural network training samples, and the spark samples needed to be identified were used for model checking. The expected output of the neural network is the type of electrical spark.

According to the universal approximation theorem [5], any three-level BP network can achieve the approximation of continuous functions on any bounded region by adjusting the number of neurons in the hidden layer [6]. Therefore, the BP neural network model for the identification of discharge spark electromagnetic waves was a three-layer BP network, the number of input layers was 5 and the number of output targets was 1 determining the hidden layer was 9.

Random numbers ranging from -0.5 to +0.5 were used as the initial weight $w$ of the network by using MATLAB. In order to ensure the BP network can learn the nonlinear relationship [7] between input and output, the Sigmoid function was used as the hidden layer transfer function and the linear function was used as the output layer transfer function [8], the learning rate of the BP network was 0.01, and the expected error of the network is 0.001. The maximum number of trainings was generally 10,000. When the number of training sessions reaches the maximum number of trainings, but it still does not converge, the training would stop [9]. The BP neural network parameters designed in this paper are shown in Table 1.

| Parameter Type           | Parameter value |
|--------------------------|-----------------|
| Hidden layer function    | Tansig          |
| Output layer function    | Purelin         |
| Maximum training times   | 10000           |
| Learning rate            | 0.01            |
| Objective function error | 0.001           |
In the BP self-learning [10], the spark sample parameters are used as training input values of the BP neural network, and the desired output value of the high-pressure discharge spark is 0, the expected output value of the low-pressure discharge spark is 0.5, and the expected output value of the glow discharge spark is 1.

The schematic diagram of the established BP network model is shown in Figure 1. There are 5 neurons in the input layer, 9 neurons in the hidden layer, and 1 neuron in the output layer.

![BP neural Network model](image)

**Figure 1.** BP neural Network model

3. Data Analysis

After establishing the BP neural network electrical spark identification model, the calculation of the model needs to be implemented through programming in matlab [11]. The identification results are shown in Table 2. There are 21 correct and 4 errors, and the correct rate is 84%. It can be concluded from the accuracy and speed of recognition. The BP neural network method has certain effectiveness and feasibility for identifying spark spark type, but its accuracy rate still needs to be improved. Especially in the identification of spark sparks and some of the more specific spark waveforms where some data is at two critical points of classification [12], it is still necessary to improve the identification capability of the network itself.
Table 2. Determination Results of the BP Neural Network

| No. | BP neural network results | BP recognition result | The actual situation |
|-----|--------------------------|-----------------------|---------------------|
| 1   | 0.0008                   | High-voltage discharge spark | High-voltage discharge spark |
| 2   | 0.1090                   | High-voltage discharge spark | High-voltage discharge spark |
| 3   | 0.2926                   | Low-voltage discharge spark* | High-voltage discharge spark |
| 4   | 0.0073                   | High-voltage discharge spark | High-voltage discharge spark |
| 5   | 0.1825                   | High-voltage discharge spark | High-voltage discharge spark |
| 6   | 0.2000                   | High-voltage discharge spark | High-voltage discharge spark |
| 7   | 0.0180                   | High-voltage discharge spark | High-voltage discharge spark |
| 8   | 0.1534                   | High-voltage discharge spark | High-voltage discharge spark |
| 9   | 0.5775                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 10  | 0.4467                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 11  | 0.3900                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 12  | 0.6840                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 13  | 0.5421                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 14  | 0.7927                   | Glow discharge spark*      | Low-voltage discharge spark |
| 15  | 0.6628                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 16  | 0.7607                   | Glow discharge spark*      | Low-voltage discharge spark |
| 17  | 0.5819                   | Low-voltage discharge spark | Low-voltage discharge spark |
| 18  | 0.8764                   | Glow discharge spark       | Glow discharge spark |
| 19  | 1.0230                   | Glow discharge spark       | Glow discharge spark |
| 20  | 0.9368                   | Glow discharge spark       | Glow discharge spark |
| 21  | 0.2359                   | High-voltage discharge spark* | Glow discharge spark |
| 22  | 0.8500                   | Glow discharge spark       | Glow discharge spark |
| 23  | 0.9453                   | Glow discharge spark       | Glow discharge spark |
| 24  | 0.1008                   | Glow discharge spark       | Glow discharge spark |
| 25  | 0.9025                   | Glow discharge spark       | Glow discharge spark |

4. Conclusion
Combined with BP neural network, a network model of discharge spark electromagnetic waves was established and analyzed and trained [13]. Through the trained network, 25 sets of discharge spark samples were identified. The recognition results were compared with the theoretical expected results, and the effectiveness and feasibility of BP neural network in the identification of discharge spark electromagnetic waves were determined. However, BP neural networks have many limitations [14]. First, there are no effective methods for determining the number of neurons in the hidden layer and the learning rate. The learning process requires continuous changes of parameters and repeated data fitting. Second, the training effect. Over-reliance on the network training samples [15], but the number of discharge spark waveforms is not sufficient, resulting in a higher rate of false positives. Third, the training process may be trapped in a local minimum.

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6. References
[1] N. Fujimoto and S. A. Boggs. Characteristics of risetime transients incident on externally connected GIS disconnect or induced short power system components [J]. Transaction on Power Delivery, 1988, 3 (3): 961-970.
[2] Delyon B, Juditsky A. Accuracy Analysis for Wavelet Approximations [C]. IEEE Transactions on Neural Networks, 1995, 6 (2): 332-348.
[3] Zoran Radojević; Vladimír Terzić Intelligent two-port numerical algorithm for transmission lines
disturbance records analysis[J] Electrical Engineering 2013-5
[4] Solar BOS; Solar BOS Passes Arc Fault Test in Livermore, CA [J]Anonymous Energy Weekly News 2011
[5] Temple, David; Joye, Ken Consulting. A look at arc-resistant switchgear [J] Specifying Engineer 2009-6
[6] Sham Sunder Srinivas Yellamraju;, Sanjay V. Kulkarni. Performance and modelling of 70kV dc power supply with solid-state crowbar [J] Fusion Engineering and Design 2013
[7] Walsh, Peter R Consulting. Calculating Arc Flash Hazard Levels [J] Specifying Engineer 2008-6
[8] C. E. R. Bruce and R. H. Golde, the Lightning Discharge [J]. J. Inst. Elect. Engrs. 1941, (88): 487-505
[9] Elio Fonseca Barbosa, Jose Osvaldo Saldanha Paulino, Glassio Costa de Miranda. Measured and Modeled Horizontal Electric Field From Rocket-Triggered Lightning [C]. IEEE Trans. Electromagn. Compat, 2008, 4 (50): 913 - 920.
[10] Pan Q. Two Denoising Methods by Wavelet Transform [C]. Signal Processing, 1999, 47(3): 3401-3405.
[11] Gedney S D. An anisotropic perfectly matched layer absorbing media for the truncation of FDTD lattices [C]. Pp1630-1639. Trans. Antennas Propagat., Dec. 1996, AP - 44 (12).
[12] Chui. C. K. Wavelet. A tutorial theory and applications [C]. New York: A Cademic Fress, 1992:1-453.
[13] Application of SVM in Analyzing the Headstream of Gushing Water in Coal Mine [J]. Journal of China University of Mining & Technology (English Edition), 2006, (04):433 - 438.
[14] Mine water discharge prediction based on least squares support vector machines [J]. Mining Science and Technology, 2010, (05):738 - 742.
[15] Removal of heavy metals from mine water by cyanobacterial calcification [J]. Mining Science and Technology, 2010, (04): 566 - 570.