Evaluation on Partial Discharge Intensity of Electrical Equipment Based on Improved ANFIS and Ultraviolet Pulse Detection Technology

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This research was supported by the National Natural Science Foundation of China (51677009) and the Chongqing Science and Technology Project (cstc2017jcyjAX0181).

ABSTRACT The ultraviolet pulse detection technology has superiorities in response speed and antijamming capability, so it is extensively applied to insulation detection for electrical equipment. The existing detection and analysis methods have defects, such as failure of precise modeling caused by incomplete analysis of influence factor, poor model adaptability, and complex operation. In allusion to the problems, the ultraviolet pulse detection circuit was optimized and its sensitivity was analyzed through tests. Then, a partial discharge intensity evaluation method for electrical equipment based on the improved adaptive network based fuzzy inference system (improved ANFIS) was proposed combined with the detected pulse count (P), temperature (T) and humidity (H). The initial fuzzy inference system structure was established with the subtractive clustering method (SCM) and fuzzy C-means (FCM) algorithm, and the traditional ANFIS learning algorithm was improved via Fletcher-Reeves conjugate gradient method. In this way, the model parameters were optimized continuously, and the system ability of ignoring small changes in the network was improved. Finally, the effectiveness and practicability of the method were verified through field test. The experimental results demonstrated that the improved ANFIS reduced the model error by 2% when compared with traditional ANFIS, and the model accuracy is improved. Besides, the quantitative precision of the discharge intensity is higher than that of the traditional ANFIS by the contrastive analysis of field test data, indicating that the improved ANFIS evaluate the partial discharge intensity of electrical equipment more accurately. Thus, a decision basis can be provided for the equipment protection and charged maintenance of the electric system.

INDEX TERMS Conjugate Gradient Method, Improved ANFIS, Partial Discharge Intensity, Subtractive Clustering, Ultraviolet Pulse Detection.

I. INTRODUCTION The safe and reliable operation of electrical equipment is directly related to its insulation conditions. Under the influences of environmental factors and electric field distortion in the operating process, the insulation will degrade easily, leading to the partial discharge phenomenon. The insulation fault of electrical equipment is the most common fault in power system. The partial discharge degradation of external insulation of high voltage electric power equipment will cause very severe accidents. Numerous experimental studies show that detecting partial discharge is an important method to discover equipment insulation fault and potential hidden dangers. Therefore, it has important significance for the safe operation of electric system to evaluate the discharge intensity of electrical equipment accurately and rapidly [1-5].

As one of the important methods to detect partial discharge of electrical equipment, the ultraviolet pulse detection method has the advantages of high response speed, strong antijamming capability, low cost and being non-contact. It is the development tendency of partial discharge detection [6]. Owing to the ability to imitate human learning and inference, the artificial neural network algorithm and fuzzy inference algorithm are successfully applied in the partial discharge intensity evaluation methods. However, the fuzzy inference system lacks an effective learning mechanism, and it has cer-
taint subjectivity when establishing fuzzy rules and membership functions, so its application has some limitation [7]. The artificial neural network is similar to a black box, lacking transparency. Although it has very strong self-study ability, it can hardly simulate the inference function of human brain. The adaptive network based fuzzy inference system (ANFIS) has combined the learning ability of artificial neural network and the logical reasoning ability of fuzzy system. Having advantages of both algorithms, it possesses better performance, but its structure is complex and the learning algorithm still has shortcomings, such as poor global searching ability, low convergence rate, and falling into local optimum easily [8-10]. To solve the above problems, the FCM algorithm was initialized via the cluster centers and the number of clusters obtained by the SCM, and the initial fuzzy inference system structure was established via the initialized FCM algorithm. Then the learning algorithm of the traditional ANFIS was improved with Fletcher-Reeves conjugate gradient method [11-13]. In this way, the model structure was simplified, and the model accuracy was improved.

Firstly, the ultraviolet pulse detection circuit for partial discharge was optimized, and the circuit sensitivity was tested, to improve the accuracy of detection data. Then an improved method of ANFIS based on SCM-FCM algorithm and Fletcher-Reeves conjugate gradient method was proposed combined with the detected pulse count (P), temperature (T) and humidity (H). Later, according to the discharge intensity J’ obtained under the laboratory conditions, the mass data of P, T, H and J’ were adopted as the training and test data of improved ANFIS system to establish the improved ANFIS model. Finally, a contrastive analysis was made on the quantitative results of discharge intensity (J) gained by the improved ANFIS model and traditional ANFIS model through the field test data and theoretical analysis. The results show that the improved ANFIS has higher prediction accuracy when applied to discharge intensity evaluation for electrical equipment via ultraviolet pulse detection, and that effective suggestions can be provided for online monitoring and overhaul of equipment insulation.

II. OPTIMIZATION OF ULTRAVIOLET PULSE DETECTION CIRCUIT

According to the ultraviolet pulse detection methods, ultraviolet photosensitive sensors used to detect the partial discharge of electrical equipment respond to the wavelength of 160-280 nm only [14-16]. Considering the process cost, working stability, sensitivity and other factors of existing ultraviolet photosensitive sensors, the R9533 solar-blinded ultraviolet photosensitive sensor was selected. R2868 is a kind of side-window ultraviolet photosensitive sensor whose sensitivity is 5000 cpm, and it has difficulties in alignment of detection angle. The sensitivity of R9533 end-window ultraviolet photosensitive sensor is higher (10000 cpm). Moreover, the end-window sensor has advantages of easy installation and easy angle alignment. Meanwhile, translucent photocathode deposits on the inner surface of the incident window, which makes it more uniform than the side window type and can effectively increase the ultraviolet flux of the ultraviolet sensor.

Based on common drive circuits of ultraviolet pulse detection [17-18], the drive circuit was optimized and the sensitivity of ultraviolet discharge detection was increased. The drive circuit is shown in Fig. 1. \( T_1 \) is the PNP triode, \( T_2 \) is the NPN triode, and CD40106 is the Schmitt trigger. According to the parameters (\( R_3=10 \, k\Omega \) and \( C_2=1000 \, pF \)) recommended for the ultraviolet photosensitive sensor, the driving power voltage was decided (\( V_{W}=350V \)). After the drive voltage was determined preliminarily, different values of \( R_3 \) and \( C_2 \) were set to obtain the optimum combination of RC. The test shows that when \( R_3=5 \, k\Omega \) and \( C_2=10 \, nF \), the change in discharge current of the ultraviolet photosensitive sensor is the smallest, and the setting effect of capacitance on output voltage is the most obvious, which is beneficial to pulse count statistics during discharge detection. The improved drive circuit increased the charging speed of \( C_2 \), shortened the quenching time, and improved the sensitivity of ultraviolet discharge detection on the original basis. The ultraviolet pulse detection device and installation of field detection device are presented in Fig. 2 and Fig. 3.

**FIGURE 1. Driving circuit of Ultraviolet photosensitive sensor.**

**FIGURE 2. Detection device of Ultraviolet pulse.**

The optimized drive circuit was installed in the monitor of the ultraviolet pulse detection device to drive the ultraviolet photosensitive sensor.
The selection of the residual clustering is the Kth clustering is a constant that defines the in which the data point. The influence of data, and its density function; its value will directly influence the \( \sum \).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2019.2938784, IEEE Access

SCM, which solves the problem that the FCM algorithm cluster centers and the number of clusters obtained from the SCM-FCM algorithm initializes the FCM algorithm via the ANFIS, it has greatly reduced the calculation amount. The compared with the default grid method of the traditional ANFIS system structure adopts the mode of grid partition for network input. In terms of complex nonlinear input, the fuzzy subset of each input into extremely small units, which high prediction accuracy must be achieved by dividing the fuzzy control are all realized through the neural network. Hence, the flexibility and adaptive capacity of the system are enhanced [19-22].

A. SYSTEM STRUCTURE IMPROVEMENT BASED ON SCM-FCM algorithm

The initial system structure has a great impact on the performance of the system and the learning efficiency. The traditional ANFIS system structure adopts the mode of grid partition for network input. In terms of complex nonlinear input, high prediction accuracy must be achieved by dividing the fuzzy subset of each input into extremely small units, which will undoubtedly cause exponential growth of fuzzy rule number and computation complexity with the increase of dimension. In order to reduce the fuzzy rule number and computation complexity, the SCM-FCM algorithm was introduced to realize non-linear dividing for the input space. Compared with the default grid method of the traditional ANFIS, it has greatly reduced the calculation amount. The SCM-FCM algorithm initializes the FCM algorithm via the cluster centers and the number of clusters obtained from the SCM, which solves the problem that the FCM algorithm needs to set the initial cluster centers and the number of clusters manually. In addition, the sensitivity of the FCM algorithm to noise points and isolated points was weakened through weighting of data points, and the accuracy of cluster centers was improved. The specific process of the SCM is as follows:

1) Consider the n data points \( \{x_1, x_2, \ldots, x_n\} \) of the M-dimensional space. Each data point is set as the candidate of clustering center, and the density function \( P_i \) in which the data point \( x_i \) is the clustering center is defined as follows:

\[
P_i = \sum_{j=1}^{n} \exp\left(-\frac{4}{r_i^2} \|x_i - x_j\|^2\right) \quad (1)
\]

In the formula, \( r_i \) is the density radius, which defines a domain of the data point \( x_i \). The influence of data points outside this radius on the possibility for this data point to be clustering center can almost be ignored.

2) Select the data point with the largest density function as the first clustering center \( x_1^c \), and its density function is \( P_1^c \). The selection of the residual clustering center must be ensured that the density function itself is large enough and far enough away from the selected clustering center. Modify the density function for the remaining data points \( x_i \) to be clustering center according to Formula (2):

\[
P_i = P_i - P_1^c \exp\left(-\frac{4}{r_i^2} \|x_i - x_1^c\|^2\right) \quad (2)
\]

In the formula, \( r_i = \eta r_i^c \) is a constant that defines the domain radius in which the density function of data points obviously decreases to avoid clustering centers that are very close together. \( \eta \) is the inhibitory factor, whose common value range is [1.2,1.5], and it’s usually taken as \( \eta=1.3 \).

3) Search continuously according to Formula (2) then, and judge whether the terminal condition is met by Formula (3):

\[
P_k^c < \delta P_1^c \quad (3)
\]

If the condition is met, it shall not be set as the clustering center, and clustering shall be stopped. If the above formula is not tenable, \( x_k \) is the Kth clustering center, and searching shall be continued. In the formula, \( 0 < \delta < 1 \); its value will directly influence the final number of clusters, and it’s usually taken as \( \delta=0.5 \).

Through the above algorithm, the initial cluster centers and the number of clusters can be obtained. Then the FCM algorithm was initialized based on these cluster centers and the number of clusters. Finally, the initial fuzzy inference...
system structure was established through the initialized FCM algorithm. Moreover, due to the different distribution of each data point and the unavoidable existence of some noise points and isolated points in the real data set, the contribution of different data points to the clustering results varies. And if the data set is sparsely distributed, its clustering effect may also be affected. Therefore, the sensitivity of the FCM algorithm to noise points and isolated points was weakened through weighting of data points with density function. The specific process of the FCM algorithm and data points weighting is as follows:

1) Combining Formula (1), the density function \( p_i \) of all data points is normalized and the weight is calculated by Formula (4):

\[
\omega_i = \frac{p_i}{\sum_{i=1}^{n} p_i} \tag{4}
\]

In the formula, \( \omega_i \) is the weight value, which is used to assign larger weight to data points with high density, and smaller weight to noise points and isolated points, so as to reduce the influence on the clustering result.

2) The number and center of clusters have been obtained by Formulas (1)–(3). On the assumption that the data set is divided into C classes, the membership degree of data point \( x_i \) belonging to clustering center \( c_j \) is \( u_{ij} \), and the objective function is established:

\[
J = \sum_{j=1}^{C} \sum_{i=1}^{n} \omega_i u_{ij}^m \| x_i - c_j \|^2 \tag{5}
\]

\[
\sum_{j=1}^{C} u_{ij} = 1, \quad i = 1, 2, \cdots, n \tag{6}
\]

In the formula, \( m \) is the smoothing coefficient, whose common value range is \([1.5, 2.5]\), and it’s usually taken as \( m=2 \). Formula (6) is the constraint of the objective function.

3) The clustering optimal solution is the case where the objective function takes the minimum value. The Lagrange multiplier method is used to search the minimum value of the objective function, and the formulas of the membership function and the clustering center are obtained:

\[
u_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{2/(m-1)}} \tag{7}
\]

\[
c_j = \frac{\sum_{i=1}^{n} \omega_i u_{ij}^m x_i}{\sum_{i=1}^{n} \omega_i u_{ij}^m}, \quad j = 1, 2, \cdots, c \tag{8}
\]

Let the iteration count be \( g=1 \), the membership degree \( u_{ij}(g) \) is calculated by Formula (7), and then revise the clustering center \( c_j(g+1) \) by Formula (8). After that, the correction error \( e = J(g+1) - J(g) \) is calculated. If \( e \) is smaller than the set tolerance error \( \varepsilon \), end the iteration; otherwise \( g=g+1 \), continue the iterative calculation. Finally, if \( \| x_i - c_j \|^2 < \| x_i - c_k \|^2 \), \( k=1,2,\cdots,c \) and \( k \neq j \), the data point \( x_i \) belongs to the \( j \)th class.

B. BP ALGORITHM IMPROVEMENT BASED ON FLETCHER-REEVES CONJUGATE GRADIENT METHOD

The learning algorithm of the traditional ANFIS is a mixed algorithm combining the standard BP algorithm with least square method. The standard BP algorithm regards the sum of the squared error of the expected output and the actual output as the target error function, searches along the opposite direction of the error gradient, and obtains the minimum value of the target error function through continuous iteration. But the standard BP algorithm has disadvantages like low convergence rate and easy to fall into local optimum. In order to make up its defects, many improved BP algorithms are proposed, and different improved algorithms are skilled at different areas. For example, the LM algorithm is suitable for dealing with the problem of few network weights, and the resilient BP algorithm can handle the issue of pattern recognition. The conjugate gradient method can be used to process the problem of too many network weights, and its prediction accuracy is even higher than that of LM and resilient BP algorithms. Therefore, the BP algorithm of traditional ANFIS was improved via Fletcher-Reeves conjugate gradient method. The steps of the algorithm are as follows:

1) The first step of the conjugate gradient method is to search along the negative gradient direction of the target error function:

\[
D_0 = G_0 = -\nabla f(W_0) \tag{9}
\]

In the formula, \( D_0 \) is the direction vector of the first step; \( G_0 \) is the direction vector of the first step negative gradient; \( \nabla f(W_0) \) is the vector of the first step gradient.

2) Then conduct linear search to determine the optimal distance of moving along the present search direction:

\[
W_{n+1} = W_n + \alpha_n D_n \tag{10}
\]

The search direction of the next step is conjugated to the current search direction, obtained from the current negative gradient direction and the search direction of the previous step:

\[
D_n = G_n + \beta_n D_{n-1} \tag{11}
\]

In the formula, \( D_n \) is the present search direction; \( W_n \) is the present weight vector; \( G_n \) is the direction vector of the current negative gradient; \( \alpha_n \) is the learning rate.
3) The different conjugate gradient methods have different calculation methods for the search step size \( \beta_n \), and it is calculated in Fletcher-Reeves conjugate gradient method by Formula (12):

\[
\beta_n = \frac{G^2_G}{G^2_{(x_{n-1})}G_{(x_{n-1})}}
\]

In order to ensure that the value of the target error function continues to decrease, the direction should be constantly corrected in the search process. As for the modification method, when the training number is an integer multiple of the weight number, \( \beta_n \) shall be 0. Meanwhile, judgment is conducted at every training step. If \( \nabla f(W_n) \cdot D_n \geq 0 \), \( D_n = -\nabla f(W_n) \). That is, the negative gradient direction is the new search direction, so as to search along the declining direction all the time. Finally, when the set target error function minimum value or the maximum number of training times is reached, the search ends.

In summary, for the system structure, the SCM takes data points as candidate sets of cluster centers, and the calculation amount is independent of the dimension of the input data, and adaptively determines the cluster centers and the number of clusters. Moreover, the FCM algorithm determines the clustering relationship by membership degree, making the clustering results more accurate. Compared with the grid method of traditional ANFIS, the calculation amount was simplified and the fuzzy rule number and system complexity were reduced. For the learning algorithm, the Fletcher-Reeves conjugate gradient method does not directly calculate the second derivative, but has quadratic convergence properties. The first step still falls in the opposite direction of the gradient, and then searches along the search direction of the previous step and the negative gradient direction of the current gradient. Compared with the standard BP algorithm of traditional ANFIS, the convergence rate was improved, and the shortcoming of easily falling into local optimal was effectively overcome.

C. IMPROVED ANFIS MODELING

1) THEORETICAL LABORATORY DATA ANALYSIS

Field test can not measure the true discharge intensity of the insulator with the partial discharge instrument. In order to analyze the relation between discharge intensity and influence factors, the functional relationship of P, T, H and \( J' \) was gained via the P, T, H and \( J' \) curve and \( P0 \) axis; \( P0 \) is the intersection point of initial curve and \( P \) axis; \( J' \) is inversely proportional to \( T \).

In the formula, \( P \) is the pulse count; \( P_{P0} \) is the intersection point of \( J' - P \) curve and \( P \) axis; \( J'_{P0} \) is the intersection point of \( J' - P \) curve and \( J' \) axis; \( K_{P} \) is a constant, and the value of \( K_{P} \) is different in different systems; \( H \) is the humidity; \( J'_{H0} \) is the intersection point of \( J' - H \) curve and \( J' \) axis; \( \alpha \) is the coefficient of exponential function, and \( h \) is the humidity corresponding to the turning point of function; \( T \) is the temperature; \( T_{H0} \) is the intersection point of \( J' - T \) curve and \( T \) axis; \( J'_{T0} \) is the intersection point of initial \( J' - T \) curve and \( J' \) axis; \( K_{T} \) is a constant, and the value of \( K_{T} \) is different in different systems. The coefficients and constants are related to the coverage of \( J' \), which are different in different external environments. Moreover, The coefficients and constants are obtained by the geometric relationship in the functional curves obtained from laboratory test data, and the values of coefficients and constants do not affect the consistency verification between the improved ANFIS model and theoretical function relations.

2) MODEL ESTABLISHMENT AND ANALYSIS

The domains of discourse of P, T and H were determined from the laboratory test data: [0, 3700], [0, 35] and [0, 100]. The FCM algorithm was initialized via the cluster centers and the number of clusters obtained by the SCM, and the initial fuzzy inference system structure was established via the initialized FCM algorithm. Meanwhile, as for the type of membership function, Gaussian membership function with relatively high evaluation precision was adopted, and the functional relation is shown in Formula (16). In the formula, \( c \) is a constant and it is the cluster centers calculated in Formula (8) after convergence, which is only used to initialize the membership function; \( \sigma \) is the standard deviation.

\[
F(x, \sigma) = \exp\left(-\frac{(x - c)^2}{2\sigma^2}\right)
\]

After the initial fuzzy inference system was established, the standard BP algorithm of traditional ANFIS was improved with Fletcher-Reeves conjugate gradient method. 300 groups of data were selected from P, T, H and \( J' \) as training and test data, the training number was set as 50, and then systematic training for sample data was completed. Finally, the trained model was tested by the selected test data which are typical and sufficiently different from the training data.

After systematic training, the 3-D observation chart for P, T, J and P, H & J was shown in Fig. 4. The relation between input (P, T and H) and output (J) can be observed through the 3-D observation chart. Under the simulation model, the discharge intensity \( J' \) corresponding to any P, T and H within
the domain of discourse can be read through the observation window of fuzzy rules. The observation window of fuzzy rules is shown in Fig. 5. The scope of $J$ is 0-1, representing the strength of partial discharge intensity, and its value is in direct proportion to the discharge intensity.

It can be seen from Fig. 4 that the simulation results about input variables ($P$, $T$ and $H$) and output variable ($J$) can meet the theoretical function formula of Section C (1) in Chapter III, indicating that the improved ANFIS algorithm is accurate and effective when used to evaluate the discharge intensity of electrical equipment.

The traditional ANFIS structure chart and the improved ANFIS structure chart are shown in Fig. 6 and Fig. 7, respectively. As shown in the two charts, the traditional ANFIS has to adopt relatively big dividing amount to realize high prediction accuracy, and the fuzzy rule number is 40. The system structure is complex and the operation speed is slow. After clustering, the fuzzy rule number of the improved ANFIS is 10, and its structural complexity is reduced greatly. Fig. 8 shows the comparison of training errors between the two algorithms. Fig. 9 shows the comparison of the output between the test data and the system model. After systematic training, the training data error of the improved ANFIS presents curve decrease, and the error decreases from 9.1% to 5.2%, while the training data error of traditional ANFIS drops from 11.4% to 7.2%. As can be seen from Fig. 9, the output of the system model is basically consistent with the output of the test data. Therefore, the trained system model is accurate and effective, and the training data error of the improved ANFIS becomes smaller, indicating that the corresponding simulation model can better reflect the actual partial discharge conditions of electrical equipment.
IV. TEST ANALYSIS AND VERIFICATION

In order to test the sensitivity of the optimized ultraviolet pulse detection system, discharge detection test was performed by the ultraviolet pulse detection method and the pulse current method. Then the field test data were collected via the ultraviolet detection device, and a comparative analysis was made on the quantitative evaluation results of discharge intensity between the improved ANFIS and traditional ANFIS through the evaluation model established. Finally, the effectiveness and practicability of the improved ANFIS evaluation algorithm were verified.

A. SENSITIVITY TEST AND ANALYSIS OF ULTRAVIOLET DETECTION CIRCUIT

Many traditional partial discharge detection methods adopt the pulse current method. The pulse current method often characterizes the discharge intensity and reflects the insulation condition with parameters such as initial discharge voltage $U_i$, apparent charge $q$, average discharge current $I$, and extinction voltage $U_e$. These are vulnerable to external interference, but the pulse current method is the only detection technology with quantitative criterion at present. The detection technology is the reference object for other partial discharge detection methods. In order to study the sensitivity of the ultraviolet discharge detection system, a comparison experiment with the pulse current method was performed using a needle-plate discharge model. Compared with parameters characterizing the discharge intensity such as apparent charge $q$, average discharge current $I$, and extinction voltage $U_e$, the initial discharge voltage $U_i$ can be measured more easily. Therefore, comparison of initial discharge voltage was conducted with the needle – plate device. In the test, the detection distance was 15 cm, and the needle – plate clearance distances were set as 1 cm, 3 cm and 5 cm, respectively, to characterize changes of the discharge intensity. The test data are shown in Table 1.

It can be seen from the above table that when the needle – plate clearance distance is 1 cm, the initial discharge voltage of discharge pulse detected by the ultraviolet pulse detection method is 1.2 kV lower than that of the pulse current method. Under the same needle – plate clearance distance, the initial discharge voltage of ultraviolet detection method is 25% (or above) lower. Besides, with the increase of the needle – plate clearance distance, the difference between initial discharge voltage of ultraviolet pulse detection and pulse current method becomes larger. The test results show that the sensitivity of the optimized ultraviolet discharge detection method is higher than that of the pulse current method, and the former is more effective for early monitoring of partial discharge.

B. FIELD TEST RESULTS AND ANALYSIS

1) In order to show the superiority of the improved ANFIS over the traditional ANFIS in accuracy and stability of discharge intensity evaluation, the two algorithms were compared with continuous data in three months, and the relative error $E_r$ and root mean square relative error $E_M$ were adopted as evaluation indexes for the prediction model precision. The formula is as follows:

$$E_r = \frac{|J_0 - \bar{J}|}{\bar{J}}$$

$$E_M = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{J_0 - \bar{J}}{\bar{J}}\right)^2}$$

2) Because of the limited space, partial data were chosen to analyze the results of the two algorithms. The evaluation results of discharge intensity obtained with the traditional ANFIS and improved ANFIS are $J_0$ and $J_1$. The comparison of partial data is presented in Table 2. Fig. 10 shows the discharge intensity curves from 1:00 to 10:00 for three consecutive days in March, Fig. 11 shows the discharge intensity curves from 14:00 to 23:00 for three days in April, and Fig. 12 shows the discharge intensity curves from 6:00 to 15:00 for three days in May.

### TABLE 1. Comparison of initial discharge voltage between ultraviolet detection method and pulse current method.

<table>
<thead>
<tr>
<th>Needle - plate clearance/cm</th>
<th>Ultraviolet pulse detection method / kV</th>
<th>Pulse current method / kV</th>
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<tbody>
<tr>
<td>1</td>
<td>3.8</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>4.9</td>
<td>6.8</td>
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<tr>
<td>5</td>
<td>6.0</td>
<td>8.2</td>
</tr>
</tbody>
</table>

### TABLE 2. Comparison of partial simulation output data for traditional ANFIS and improved ANFIS.

<table>
<thead>
<tr>
<th>Group</th>
<th>Time</th>
<th>Input</th>
<th>Traditional ANFIS output</th>
<th>Improved ANFIS output</th>
<th>Traditional ANFIS relative error</th>
<th>Improved ANFIS relative error</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>T</td>
<td>H</td>
<td>$J_0$</td>
<td>$J_1$</td>
<td>$E_{r0}$</td>
<td>$E_{r1}$</td>
</tr>
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<table>
<thead>
<tr>
<th>Group</th>
<th>Number</th>
<th>Duration</th>
<th>F1</th>
<th>F2</th>
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<th>F4</th>
<th>F5</th>
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<td></td>
<td>6</td>
<td>1343</td>
<td>17</td>
<td>62</td>
<td>0.792</td>
<td>0.788</td>
<td>0.3%</td>
<td>0.4%</td>
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<td>7</td>
<td>2021</td>
<td>18</td>
<td>58</td>
<td>0.890</td>
<td>0.835</td>
<td>10.8%</td>
<td>6.4%</td>
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<td></td>
<td>8</td>
<td>1959</td>
<td>20</td>
<td>49</td>
<td>0.873</td>
<td>0.854</td>
<td>9.9%</td>
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<td>0.802</td>
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in a certain scope within a period under normal situations. In Fig. 10, the three groups of discharge intensity curves present a relatively small fluctuation range, which are stabilize around 0.6. By the calculation, the root mean square relative errors $E_M$ of curves of Group 1, 2 and 3 of improved ANFIS algorithm are 7.8%, 5.7% and 7.1%, decreasing by 2.1%, 1.7% and 3.8% when compared with that of the traditional ANFIS algorithm. Therefore, the evaluation curve fluctuation of the improved ANFIS is smaller, and it has higher stability in discharge intensity evaluation.

According to the comparison of curves in the same group in Fig. 11, i.e. the comparison of discharge intensity evaluated with the traditional ANFIS and improved ANFIS, the average relative errors of curves of Group 1, 2 and 3 drop from 8.85%, 6.65% and 9.94% to 6.81%, 5.24% and 6.54%. Also in Fig. 12, the average relative errors of curves of Group 1, 2 and 3 drop from 7.3%, 14.7% and 9.0% to 6.2%, 7.7% and 9.0%. Hence, the evaluation curves of the improved ANFIS have a smaller mean deviation and more accurate result in discharge intensity evaluation. It can reflect the partial discharge intensity changes of the insulator more truly.

As can be seen from Table 2 and Fig. 12, the discharge intensity from 9:00 to 10:00 in the second group of data rises suddenly from 0.3 to 0.7, and the follow-up discharge intensity is about 0.65, indicating that the partial discharge intensity may be strengthened and the insulation performance of insulating equipment may drop. Later, the veracity of its discharge intensity evaluation was verified through insulation repair results at the site. Besides, under the sudden change of partial discharge intensity, after the improved ANFIS analysis and modeling, the maximum relative error in this group of data became 18.1%, decreasing by 14.6% when compared with that of the traditional ANFIS. This further shows that the improved ANFIS algorithm has higher accuracy than the traditional ANFIS algorithm when evaluating the discharge intensity of electrical equipment.

V. CONCLUSION
Based on the research of traditional ANFIS and ultraviolet pulse detection technology, the selection of UV sensor and circuit parameters were optimized. Then, an improved ANFIS algorithm was proposed to realize accurate measurement for the partial discharge intensity of electrical equipment. The initial fuzzy inference system structure was established via the SCM-FCM algorithm, and the learning algorithm of the traditional ANFIS was improved via Fletcher-Reeves conjugate gradient method. Finally, the improved model was established and field test conducted. The following conclusions were drawn:

1) The R9533 side-window ultraviolet photosensitive sensor with higher ultraviolet light flux, easy installation and easy angle alignment was used to expand the dynamic detection scope. Parameters of the drive circuit were optimized to increase the charging and dis-
charging rate of the drive circuit. The system sensitivity is higher than that of the pulse current method, which is more effective for early detection of partial discharge.

2) The improved ANFIS has reduced the fuzzy rule number and system complexity, and overcome the defects of the standard BP algorithm including falling into local optimum easily and low convergence rate. Moreover, it has reduced the model error by 2% when compared with the traditional ANFIS, and improved the model accuracy.

3) Through the comparison of field test data, the improved ANFIS has increased the accuracy and reliability of evaluation results. Meanwhile, it has enhanced the applicability of the evaluation results. Therefore, the improved ANFIS algorithm shows higher prediction accuracy when applied to the evaluation of electrical equipment discharge intensity by ultraviolet pulse detection, and it can provide valuable reference information for on-line monitoring of insulation condition and insulation maintenance.

REFERENCES


Jingang Wang received the Ph.D. degree from Chongqing University. He is currently a professor of electrical theory and new technology at the College of Electrical Engineering, Chongqing University. He is mainly engaged in electromagnetic field measurement and calculation, weak signal measurement and processing, high-voltage equipment discharge detection technology, power system operation and control research. He has presided over two projects of the National Natural Science Foundation of China, two projects at provincial and ministerial levels, and participated in international cooperation projects and national 863 projects. He has published more than 50 academic papers, more than 30 core SCI and EI papers, and more than 10 invention patents. He is also a reviewer of "Journal of Electrical Engineering", "Journal of Electrical Engineering", "Sensor", "IEEE Sensor", "Sensor Review" and "International Emerging Power System Journal".

Peiyuan Li received a bachelor's degree in electrical engineering from Xihua University. He is currently a second-year graduate student in the Department of Electrical Theory and New Technology at the School of Electrical Engineering, Chongqing University. The research direction is mainly electromagnetic measurement and instrumentation, fault diagnosis and operational risk assessment. Participated in 1 Chongqing Science and Technology Project and 1 National Natural Science Foundation Project.

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