An Intelligent Fault Diagnosis Method for CNN-SVM Circuit Breaker Based on Quantum Particle Swarm Optimization

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Abstract. In order to make use of fewer fault data samples to diagnose the main fault types of circuit breakers accurately in real time, an intelligent fault diagnosis method for circuit breakers based on convolutional neural network (CNN) and quantum particle swarm optimization (QPSO) is proposed. Firstly, the key features of the circuit breaker operational signal are extracted through the CNN model, and the extracted feature vectors are input into the support vector machine (SVM) for fault diagnosis. In order to improve the diagnostic performance, this paper uses QPSO algorithm to optimize the parameters of the classifier, it effectively solves the local optimal problem. The experimental results show that the method presented in this paper has achieved good results in fault diagnosis of circuit breakers, and the accuracy of diagnosis is up to 100%, which highlights the superiority of this method.

1. Introduction
As an important power equipment, the working state of circuit breaker directly affects the safety of the power system. According to relevant data, more than 2/3 of circuit breaker failures are caused by abnormal operation of the operating mechanism[1]. Traditional manual patrol mode always bring unnecessary shutdown, in the context of smart grid, major power equipment manufacturers have increased research efforts on circuit breaker fault diagnosis technology. There are abundant vibration signals in the operation of circuit breakers. Taking the vibration signals during charged operation as input signals, the characteristic factors representing the state can be effectively extracted and used to analyze the fault location of circuit breakers, so as to realize state monitoring and diagnosis of circuit breakers[2].

As for the selection of fault diagnosis algorithms, most of the current artificial intelligence algorithms are machine learning. In Literature[3], Back Propagation (BP) algorithm and Radial Basis Function (RBF) were used to carry out fault diagnosis of circuit breakers, and the results showed that RBF neural network had fast training speed and good classification performance. In literature[4], wavelet packet transform was used for data preprocessing, and then Particle Swarm Optimization (PSO) algorithm and RBF were combined to build fault diagnosis network for circuit breakers. The accuracy of RBF network model after PSO was higher than that of RBF neural network. Although the diagnostic accuracy of traditional algorithms has been greatly improved, these algorithms generally have problems such as slow diagnosis speed and poor generalization ability, which limits the development of fault diagnosis technology of circuit breaker.
Because the traditional artificial intelligence algorithm still has many defects, this paper proposes an intelligent fault diagnosis method of circuit breaker based on convolutional neural network (CNN) and quantum particle swarm optimization (QPSO). This method is based on the CNN, using the circuit breaker operational signal data as the training sample to train the CNN model. The trained CNN model is combined with the QPSO algorithm to optimize the parameters of the SVM classification model, and the optimal parameters are outputted while CNN parameters remain unchanged. The SVM fault classification model was built based on the optimal parameters, and the test samples were input to the CNN-QPSO-SVM model, and the final fault diagnosis results were output.

2. Convolutional neural network model

Inspired by the human brain’s processing of the external information received, LeCun proposed the convolutional neural network (CNN) model for the first time in 1994[5]. CNN model consists of convolutional layer, pooling layer and full connected layer, as shown in figure 1.

The convolutional layer has the characteristics of local perception and weight sharing, and the network parameters to be trained can be greatly reduced to reduce the amount of calculation. The operation of the convolution layer is as follows:

\[ X_j^l = f \left( \sum_{i=M_j} x_{i}^{l-1} \ast K_{ij}^l + B^l \right) \]

where \( x_{i}^{l-1} \) is a feature in the filter of the upper layer, \( M_j \) is the filter corresponding to neuron \( j \), \( K_{ij}^l \) is the \( J \)th corresponding weight of neuron \( I \) in layer \( l \), \( B^l \) is the unique offset of layer \( l \), and \( f(x) \) is the activation function. Common activation functions are sigmoid, tanh, and ReLU, and the ReLU activation function is usually chosen.

The pooling layer is used to reduce the size of the feature map and reduce the number of parameters to be trained by reducing the dimension of the feature map. The pooling layer enhances the robustness of feature extraction through the lower sampling factor. The pooling function is expressed as \( \text{downsample()} \). For each \( x_j^l \), there is:

\[ X_j^L = \text{downsample}(x_j^l) \]

After the convolution layer and the pooling layer, several full connected layers are usually connected, with the purpose of integrating the local feature information in the convolution layer or the pooling layer that can effectively distinguish the different categories. In order to improve the overall performance of CNN, the activation function of the full connected layer generally adopts the ReLU function. Its feedforward process is the same as that of the standard artificial neural network (ANN), as shown in equation (3).

\[ x_j^l = f \left( \sum_{i=1} w_{ji} x_{i}^{l-1} + B^l \right) \]

where \( w_{ji} \) is the weight of node \( j \) at layer \( l \) to node \( i \) at layer \( l+1 \).

The final layer of the neural network generally uses the softmax classifier to classify the different categories of data. The feature vectors with a fixed dimension are the output of the previous layer and serve as the input to the softmax classifier, which converts the output of the last layer into a basic probability distribution to predict the class labels of the input data.

![Figure 1. Convolutional neural network structure.](image-url)
3. Support vector machine

Support Vector Machine (SVM) has good generalization performance and classification accuracy. The principle of SVM is to map data from a low-dimensional space to a high-dimensional space and find a hyperplane that can effectively divide samples of different categories. This hyperplane maximizes the minimum distance from a point in the data set to this surface, that is, find the maximum classification interval. Finally, the hyperplane corresponding to all the maximum classification intervals is determined to achieve the classification of the sample set [6].

By introducing kernel function to deal with various nonlinear problems, SVM shows good generalization ability in the training set and achieves high accuracy. There are four kinds of kernel functions commonly used: linear kernel function, polynomial kernel function, sigmoid kernel function and radial basis kernel function [7]. Radial basis function (RBF) was used as the kernel function of SVM in this paper, and the RBF expression is shown in equation (4).

\[ k = \exp(-\gamma \cdot d^2) \]  

(4)

where \( d \) represents the distance between two points. The bigger the \( \gamma \), the fewer the support vectors, the smaller the \( \gamma \), the more support vectors. The number of support vectors influences the speed of training and prediction.

SVM selects \( \gamma = 0.1 \) and \( C = 0.8 \) as parameters. Where \( C \) is the penalty coefficient, namely the tolerance to error. The higher \( C \) is, the less errors can be tolerated and the overfitting is easy. The smaller \( C \) is, the easier it is to underfit.

4. Quantum particle swarm optimization algorithm

In order to make the classification of fault diagnosis classifier more accurate, this paper uses the quantum particle swarm optimization (QPSO) to optimize the SVM parameters. Sun Jun first introduced quantum behavior into PSO algorithm and proposed QPSO algorithm in 2004 [8].

QPSO algorithm introduces the quantum idea that the particle can appear at any position in the search space, and the probability of appearing at a certain position is determined by a distribution function. The specific position of particles in each generation is determined by an "observation" operation. In terms of algorithm implementation, Monte Carlo method is used to recurse the specific position of particles in the n+1 generation in the nth iteration.

The central point introduced by the QPSO algorithm is shown in equation (5).

\[ m_{best} = \frac{1}{M} \sum_{i=1}^{M} P_i \]  

(5)

where \( m_{best} \) is the average historical best position of particles. Equation (6) and equation (7) are used in the update process.

\[ P_i(t+1) = \phi P_i(t) + (1-\phi)P_g(t) \]  

(6)

\[ X_i(t+1) = P_i(t+1) + \lambda |m_{best} - X_i(t)| \ln(1/u) \]  

(7)

where \( \phi \) and \( u \) are random variables and are uniformly distributed on (0,1): the probability of getting positive and negative is 0.5. \( \lambda \) is the only control parameter, in practical application, the value of \( \lambda \) is generally less than 1, which will affect the convergence rate of the population.

QPSO algorithm introduces the degree of evolution and degree of aggregation of particles to modify parameter \( \beta \) to avoid premature convergence.

(1) Evolution rate \( e \) of particle swarm is defined as:

\[ e = \frac{\min\{p_{g}(T-1), p_{g}(T)\}}{\max\{p_{g}(T-1), p_{g}(T)\}} \]  

(8)

where \( e \) is the evolution rate factor, and \( p_{g}(T) \) is the global optimal solution of the T generation particle swarm.
(2) The degree of particle aggregation \( c \) is defined as:

\[
c = \frac{\min\{ p_x(T), p_y(T) \}}{\max\{ p_x(T), p_y(T) \}}
\]

where \( c \) is the particle aggregation factor, and \( p_x(T), p_y(T) \) are the average values of the current individual optimal solution of all particles.

The relation expression of \( \beta, c \) and \( e \) is:

\[
\beta = \beta_0 + c \beta_e - e \beta_e
\]

where \( \beta_0 \) is the initial value of \( \beta \), usually \( \beta_0 = 1 \), and \( \beta_e, \beta_e \) are random numbers between \([0,1]\).

To sum up, if the evolution rate of particle swarm slows down, the value of \( \beta \) can be reduced in order to search the particle swarm in a small space. If the degree of particle swarm aggregation increases, the particle swarm should be dispersed, the search space should be enlarged, that is, the value of \( \beta \) should be increased, so as to avoid falling into the local optimal solution.

5. Experiment and result analysis

5.1. Experimental data set

The data set in reference[9] was used for verification in this paper. The acceleration sensor was used to record the vibration acceleration parameters during the opening/closing process of the circuit breaker. The sampling frequency was 10kHz. A total of 7 groups of vibration signal data were collected, including 4 main fault types of circuit breakers. Seven experiments were conducted under each condition. Typical signals of circuit breakers in normal and fault states are shown in figure 2, and the four fault types and their serial numbers are shown in table 1.

| Fault types                              | Fault number |
|------------------------------------------|--------------|
| Normal state                             | 0            |
| Tripping to close the electromagnet blocking state | 1            |
| Spindle clogging state                   | 2            |
| Half shaft clogging state                | 3            |

(a) Normal state. (b) Tripping to close the electromagnet blocking state.
In seven data sets, three of them are selected as training dataset and the remaining four are selected as test dataset for each state.

5.2. CNN-QPSO-SVM model construction
The circuit breaker fault diagnosis method flow based on CNN and QPSO is shown in figure 3.

Figure 3. Flow chart of circuit breaker fault diagnosis method based on CNN and QPSO.
In this model, the fault sample data of circuit breakers are input into the corresponding sample data of 4 state types, and these sample data are divided into two groups, one group as the training sample and the other group as the test sample. The specific process is as follows:

1. Vibration signals of circuit breakers in normal state, tripping to close the electromagnet blocking state, spindle clogging state, half shaft clogging state were collected and used as original vibration signals for model training.

2. The original signal is normalized, as shown in equation (11).

\[ x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, i = 1, 2, \ldots, n \]  

where \( x_i \) is the original sample data, \( x_{\max} = \max(x_i) \), \( x_{\min} = \min(x_i) \). In order to find the optimal parameter combination of SVM, the normalized samples were classified, and part of the samples were selected as the training data set and the rest as the test data set.

3. The training data set is used to train CNN, and the loss function of CNN is based on the cross-entropy loss function of softmax. The specific training method is Adam gradient descent method, the batch size is 2, and the number of iterations is 200. After the completion of the training, the parameters of the CNN model are kept unchanged.

4. The trained CNN model is combined with the QPSO algorithm to train the SVM classification model. In the iteration process, the adaptive value deviation of each generation of particles is tracked in real time. If the deviation of a generation is less than the threshold value, interference operation is carried out on the average optimal position to enhance the global optimization ability of the algorithm. The algorithm outputs the optimal SVM parameters until the algorithm meets the termination condition.

5. The SVM fault classification model was built based on the optimal parameters. The test samples were input into the CNN-QPSO-SVM model and the fault diagnosis results were output.

The neural network structure constructed by this model is shown in figure 4. It can be seen from the figure that the CNN network designed in this paper has 6 convolution layers, 4 pooling layers, 1 output layer and 1 softmax layer, among which the structural parameters of each layer are shown in table 2.

![Figure 4. Structure diagram of CNN.](image)

| Serial number | Network layer name                  | Size of convolution kernel | Number |
|---------------|-----------------------------------|--------------------------|--------|
| C1            | Convolution layer1                | 8×1                      | 16     |
| C2            | Convolution layer2                | 8×1                      | 16     |
| P1            | Max pooling layer1                | 2×1                      | 16     |
| C3            | Convolution layer3                | 4×1                      | 32     |
| C4            | Convolution layer4                | 4×1                      | 32     |
| P2            | Max pooling layer2                | 2×1                      | 32     |
| C5            | Convolution layer5                | 4×1                      | 64     |
| C6            | Convolution layer6                | 4×1                      | 64     |
| P3            | Max pooling layer3                | 2×1                      | 64     |
| P4            | Global Average Pooling layer1     | -                        | -      |
| FC1           | Softmax                            | 4                        | 1      |
5.3. Experimental analysis
The trained CNN-QPSO-SVM model is used to detect the fault data sets of the circuit breakers in four different states. Finally, the simulation graph of the accuracy of the CNN-QPSO-SVM model on the verification samples is obtained. Figure 5 shows the result of the change of accuracy of training set and test set with the number of iterations. It can be seen from the figure that when the number of iterations is 25, the accuracy tends to the maximum and then becomes stable. The curve of the verification set can completely fit the curve of the training set, and there is no over-fitting or under-fitting phenomenon, and the model has been effectively learned. At the same time, cross entropy loss function is used as the loss rate calculation method, and the loss rate of the test set is obtained as shown in figure 6. It can be seen from the figure that when the number of iterations is 25, the loss rate tends to the minimum value and then becomes stable. The curve of the verification set can fit the curve of the training set perfectly, and there is no over-fitting or under-fitting phenomenon.

In order to verify the superiority of the CNN-QPSO-SVM algorithm proposed in this paper, CNN-LSTM algorithm[9], CNN-SVM algorithm and SVM algorithm are respectively used to compare with this algorithm, and the results obtained are shown in table 3.

It can be seen from table 3 that the prediction accuracy of CNN-QPSO-SVM algorithm is 100%, while the prediction accuracy of CNN-SVM or SVM algorithm is 75% and 50% respectively, which cannot effectively identify the fault type. It shows that QPSO parameter optimization has a great influence on the improvement of prediction accuracy of CNN and SVM algorithms. In addition, although the prediction accuracy of CNN-QPSO-SVM algorithm and CNN-LSTM algorithm[9] are both close to 100%, the one-dimensional convolutional neural network is better than the two-dimensional convolutional neural network in the characterization of circuit breaker vibration signals. Therefore, CNN-QPSO-SVM algorithm has a higher recognition accuracy than CNN-LSTM algorithm. Through the above comparison, it can be concluded that CNN-QPSO-SVM algorithm has the best performance among these algorithms.

6. Conclusion
In view of the difficulties in obtaining vibration signals, the lack of fault samples and the inaccurate identification of eigenvectors during the operation of circuit breakers, a circuit breaker fault diagnosis method based on CNN and QPSO is proposed in this paper. The method uses CNN moedel to extract
circuit breaker signal features effectively. Furthermore, the QPSO algorithm is used to effectively eliminate the local optimal phenomenon. Finally, SVM is used to classify the samples so that the model can diagnose the fault categories of circuit breakers effectively and accurately. The experimental results show that CNN-QPSO-SVM model can extract effective feature vectors more accurately than the other three models, and make more accurate diagnosis of feature vectors. Moreover, with the increase of the number of samples, it can still maintain a high diagnostic accuracy. In the future work, the signal preprocessing method can also be further studied, so that the model can show better performance in a more complex environment.

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