The Research on Breaker Fault Status Parameter Classification of Improved Particle Swarm Optimization

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Abstract. In order to improve the mechanical structure of the type of fault resolution precision high voltage circuit breaker spring mechanism, the paper analyzes the characteristics of the circuit breaker and the combination of mechanical vibration signal PSO algorithm (PSO) SVM parameter optimization method proposed collaborative dynamic acceleration constant inertia weight particle swarm optimization (WCPSO) optimization support vector machine (SVM) analysis breaker fault classification parameters and kernel function parameters. The vibration signal circuit breaker empirical mode decomposition, the total intrinsic mode components through energy analysis to obtain the required fault feature vectors and support vector machine as input, the use of dynamic acceleration constant synergy inertia weight PSO support vector machines penalty factor C and radial basis kernel function parameters $\sigma$ optimize the fault feature vector signal input test samples after SVM training sample trained optimized for fault classification, fault status classification.

Introduction

With the maturity distribution automation systems, circuit breakers and distribution system as an important device has important significance for its fault diagnosis. Mechanical vibration signals generated breakers in sub-closing action contains a lot of state information, has important practical implications for the analysis of vibration signals of these [1]. These frontier of contemporary theories and methods will inevitably penetrate into the diagnostic techniques in the past, making the diagnosis can almost simultaneous development of these frontier[2-3]. Swarm intelligence optimization technology as a new technology, is a new hot field of artificial intelligence research, which will be used in PSO breaker fault diagnosis, a new hotspot[4-7]. Social insects swarm intelligence is inspired by a series of new solutions to complex problems through traditional simulation generated by their actions, it is the simple dumb many groups of individuals by a simple mutual cooperation between the intelligent behavior exhibited. Among them, the PSO[8] (Particle Swarm Optimization, PSO) is a J.Kennedy and RCEberhart proposed in 1995 based on the principle of swarm intelligence optimization algorithms, It converges fast, easy to implement and only a few parameters need to be adjusted, and thus was put forth to become intelligent optimization and evolutionary computing a new hotspot[9-11].

How to use effective mathematical tool for runtime behavior of PSO, convergence, convergence speed, parameter selection, parameter robustness and computational complexity of the analysis should be the current research focus[5].

Feature Vectors Extracted Based on the Total Weight of Energy by IMF

According to the test signal and the theoretical knowledge known techniques, regardless of the actual dimensions in the case of the oscillating signals $x(t)$ time integral of the square of $x^2(t)$ is called the energy of the signal:

$$Q(i) = \int_{-\infty}^{\infty} |x(t)|^2 \, dt$$  \hspace{1cm} (1)
When the signal is \( x(t) \) discrete signal, the signal energy value added and interval signal, namely:

\[
Q(i) = \sum_{i=1}^{n} x^2(t) |\Delta t|
\]  

(2)

Where \( \Delta t \) is the sampling interval, the sampling interval is herein 0.05ms, \( Q(i) \) is the total energy of the signal on the whole interval segment.

Fault classification process block diagram shown in Figure 1, the signal is first collected for EMD decomposition, IMF and extract feature vector component fault signal input in learning good SVM classification.

![Figure 1. Process of state detection.](image)

(1) The original vibration signals of EMD, take the first n IMF component contains major faults, this paper takes the first six IMF components.

(2) Calculation of each IMF (discrete signal) a total energy component \( Q(i) \):

\[
Q(i) = \sum_{i=0}^{n} c_i^2(t) dt
\]  

(3)

(3) The components of the total energy for IMF normalized:

\[
E_i = \frac{Q(i)}{E}
\]  

(4)

Where \( E_i \) is the total energy IMF component, \( E \) is the total energy of the original vibration signal.

(4) IMF component to the total energy of the element structure eigenvectors \( T \):

\[
T = [E_1, E_2, ..., E_n]
\]  

(5)

(5) Collaborative dynamic acceleration constant inertia weight PSO optimized SVM get better classification performance, using the training data SVM training.

(6) The fault input feature vectors of training samples tested in good optimized SVM, given the state of the circuit breaker failure type.

**Collaborative Dynamic Acceleration Constant Inertia Weight Coefficient Particle Swarm Optimization Method**

PSO tend to search the optimal solution is composed of two random acceleration constant cognitive factors and social factors \( c1 \) \( c2 \) guidance, \( c1 \) and \( c2 \) represent the stochastic particle acceleration value to their extreme right and extreme global advance. If \( c1 = c2 = 0 \), then the particles will be flying this speed until the border. In this case, the particles can only search a limited area, it is difficult to find a good solution. When \( c1 = 0 \), then no cognitive particles in particle interactions, the ability of the new algorithm search space. Its faster convergence rate than the standard algorithm, but encounter complex problems more easily than the standard algorithm into local pole. When \( c2 = 0 \), there is no sharing of information between the community particles, a size of the group is equivalent to running m a single particle, thereby obtaining a very low probability of the optimal solution.

Elementary particle swarm optimization algorithm for updating the formula:

\[
v_{i+1} = v_i + c1 r1 (p_i - x_i) + c2 r2 (p_n - x_i), i = 1, 2, ...
\]  

(6)
Constant optimization of the dynamic equation and particle update formula:

\[ c_1 = R_1 + R_2 \cdot \frac{t}{T_{\text{max}}} \quad c_2 = R_3 - R_4 \cdot \frac{t}{T_{\text{max}}} \]  \hspace{1cm} (7)

R1, R2, R3, R4 as the initial setting. \( t \) is the current update algebra, \( T_{\text{max}} \) is the maximum update algebra. Wherein the selection is to select the initial setting of the simulation function calculated by the algorithm in the optimal range of values.

\[ v_{i,k}^{t+1} = \omega v_{i,k}^t + c_1 r_1 (p_{i,k}^t - x_{i,k}^t) + c_2 r_2 (p_{n,k}^t - x_{i,k}^t), \quad i,k = 1,2,... \]  \hspace{1cm} (8)

\[ x_{i,k}^{t+1} = x_{i,k}^t + v_{i,k}^{t+1} \quad i, \ k = 1,2,...n \]  \hspace{1cm} (9)

Where \( \omega \) is a coefficient of inertia weight, acceleration constants \( c_1, \ c_2 \) are non-negative constants, \( r_1, r_2 \) uniformly distributed random numbers 0-1 on.

4 Improved PSO_SVM breaker fault condition in the classification

The number of employed population particle swarm is 30, the maximum is 300 algebra. \( R_1 = 1.2, \ R_2 = 0.6, \ R_3 = 5, \ R_4 = 2.2 \) for the analysis and optimization functions by generalized derived this number is dynamic acceleration constant optimization best initial settings, \( \omega = 0.8 \) (typically 0.4-values between 1.2). Kernel function using radial basis function, Fitness function is the accuracy verify under the cross-classification.optimized SVM penalty factor \( C \) and radial basis function \( \sigma \), optimization steps are as follows:

(1) the optimization of the parameters \( C \) and \( \sigma \), the value range is constraint \( C : 0.1-1000, \ \sigma : 0.01-100 \), in the definition of the space 30 are randomly generated initial population of particles: pop \((i,1) = x_1, x_2, \ldots, x_i \) and pop \((i,2) = y_1, y_2, \ldots, y_i \). Set the maximum evolution generation \( T_{\text{max}} = 300 \), the current evolution algebra set \( t = 1 \), by formula (10) to calculate the initial value of dynamic acceleration constants \( c_1 = 1.22, \ c_2 = 4.93 \), produce changes in the composition of the initial displacement of each particle displacement matrix:

\[ \text{pop}(i,j) \quad i=1,2,...,30; \ j=1,2 \]  \hspace{1cm} (10)

(2) the use of the fitness function, namely to verify the accuracy of cross-classified under the calculated fitness value of each particle.

(3) compare the fitness value of particles and their optimal values. If the current value is better than their own, then set to the current value.

Optimization results obtained by SVM classification carried out in the breaker failure status classification, and then compare optimized.

**Experimental Results and Analysis**

WCP-SO-SVM using particle swarm optimization algorithm for support vector machine parameters and kernel function parameters were optimized.

30 sets of test data for each failure, each of 20 randomly selected as the training data set SVM training, and the remaining 10 groups each test as the test data analysis. Results of the test results takes 10, as shown in Table 1.
Table 1. WCPSO parameter optimization results.

<table>
<thead>
<tr>
<th>WCPSO</th>
<th>C</th>
<th>(\sigma)</th>
<th>Classification accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>278</td>
<td>2</td>
<td>82.5</td>
</tr>
<tr>
<td>2</td>
<td>78</td>
<td>0.9</td>
<td>92.5</td>
</tr>
<tr>
<td>3</td>
<td>78.1</td>
<td>85.3</td>
<td>85</td>
</tr>
<tr>
<td>4</td>
<td>54.8</td>
<td>0.9</td>
<td>97.5</td>
</tr>
<tr>
<td>5</td>
<td>49.2</td>
<td>32</td>
<td>87.5</td>
</tr>
<tr>
<td>6</td>
<td>12.6</td>
<td>6</td>
<td>92.5</td>
</tr>
<tr>
<td>7</td>
<td>27.9</td>
<td>65</td>
<td>90</td>
</tr>
<tr>
<td>8</td>
<td>569</td>
<td>33.6</td>
<td>92.5</td>
</tr>
<tr>
<td>9</td>
<td>113</td>
<td>21.9</td>
<td>77.5</td>
</tr>
<tr>
<td>10</td>
<td>27</td>
<td>47.3</td>
<td>75</td>
</tr>
</tbody>
</table>

As can be seen from the table when the SVM penalty factor \(C = 54.8\) and radial basis function \(\sigma = 0.9\), the performance out of the classification accuracy, highest performance.

Table 2. Classification parameters compare.

<table>
<thead>
<tr>
<th>Parameters to be optimized</th>
<th>No optimization</th>
<th>PSO</th>
<th>WCPSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>(C)</td>
<td>100</td>
<td>36.9</td>
<td>54.8</td>
</tr>
<tr>
<td>(\sigma)</td>
<td>2</td>
<td>0.9</td>
<td>1.4</td>
</tr>
<tr>
<td>Classification accuracy(%)</td>
<td>78.1</td>
<td>85.3</td>
<td>92.6</td>
</tr>
<tr>
<td>Classification time(s)</td>
<td>44.3</td>
<td>35.5</td>
<td></td>
</tr>
</tbody>
</table>

In order to verify the advantages WCPSO this optimization method, firstly no parameter optimization of SVM, PSO parameter optimization of SVM and SVM parameter optimization WCPSO the training and test data were analyzed. SVM uses "many" classification thinking, as opposed to other methods, it can better control the classification accuracy. As Table 2 shows, Time refers to the classification table from iteration to optimize the completion time classification, for optimizing the classification function without taking 100 penalty factor \(C\) and radial basis function parameter \(\sigma\) optimization results take 2; classification function for PSO take 36.9 penalty factor \(C\) and radial basis function parameter \(\sigma\) takes 0.9 optimization results; for WCPSO classification function takes the penalty factor \(C\) 54.8 and optimization results RBF kernel function parameter \(\sigma\) takes 1.4. Time refers to the classification table from iteration to optimize the completion time classification.

Optimize the classification of 20 times the average time for comparison, after the lapse of the SVM WCPSO optimized SVM classification data showing the time of the advantages of short computation time.

**Conclusion**

In this paper, the dynamic acceleration constant collaboration with inertia weight PSO optimized SVM classification function parameters \(C\) and kernel function parameters to improve the performance of the PSO algorithm. IMF component of total energy use as feature vectors characterizing the breaker failure, and as the input feature vectors of SVM, particle swarm algorithm optimized SVM classification, the classification results obtained. Results of comparative experiments show that for high voltage circuit breaker spring mechanism actuator mechanical failure vibration signals, this method can effectively improve the classification accuracy of fault classification and the state, to get a good classification results.
References


