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Fault Line Selection Method for Resonant Grounding System Based on Improved PSO-SVM

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Abstract: The fault line selection of traditional resonant system method has low reliability and poor accuracy. Although the ordinary intelligent line selection method improves the line selection accuracy, the system has a long running time and is not effective. In this paper, an improved intelligent line selection method based on particle swarm optimization (PSO-SVM) is proposed. The traditional particle swarm optimization algorithm is improved, which makes the SVM model parameters faster and less likely to fall into local optimum. Combining the fifth harmonic method and the wavelet packet variation method to achieve efficient selection of grounding faults in resonant systems. The simulation results show that the proposed method has high accuracy and is not affected by factors such as grounding resistance and fault distance.

1. Introduction

The reliability of power supply has become the focus with the development of power grid technology and the improvement of power quality requirements by user, and the rapid and accurate line selection of power distribution system line faults has become a research hotspot[1][2].The common line selection method is not suitable for the neutral point resonant ground fault system, and the line selection method based on the fault steady state feature could be adopted. However, due to the non-directionality of the current compensation of the arc suppression coil, the zero sequence current amplitude method are not applicable to the resonant grounding system. Moreover, because a single harmonic method is difficult to achieve satisfactory results due to interference from harmonic sources in the load, the harmonic method is also not applicable [3, 4]. And then some scholars find that wavelet packet changes are more suitable for resonant grounding systems[5][6]. However, the line selection efficiency of these line selection methods is not high enough, and the correctness cannot be guaranteed.

Traditional intelligent line selection methods such as neural network, D-S evidence theory, fuzzy theory are too complex and take too much time[7].and the particle swarm optimization algorithm will easily fall into the local optimal solution and cannot achieve the optimal line selection result. In this paper, an improved method is proposed to further improve it so that it is not easy to get into the local solution and is more likely to reach the optimal solution. Combining with the fifth harmonic method and wavelet transform method to selective the fault line[9]. After simulation, the improved particle swarm optimization algorithm has good results for fault line selection of resonant system. The line selection speed is high, the accuracy is good, and it does not need to consider the influence of other factors such as grounding resistance, and has good performance.

2. Material and Methods

2.1. Fault Eigenvalue Calculation

The wavelet packet transform can obtain the decomposition sequence with arbitrary frequency band compared with the wavelet transform, the wavelet packet 4-layer decomposition can obtain the optimal available fault eigenvalues. Therefore, for the zero-sequence current signal of each line in the resonant grounding system of the distribution network, the db5 wavelet packet is decomposed by 4 layers, and the transient energy fault characteristic is

$$X_1 = \varepsilon_k / \varepsilon_p \qquad (1)$$

Here, ε_k is the energy of line k in the energy concentration band, ε_p is the sum of the energy of all lines in their respective energy concentration bands.

The zero-sequence current amplitude can be used for fault line selection, and the FFT transform is used to perform Fourier transform on the line zero-sequence current[10]. Wave component eigenvalues:

$$X_2 = I_{1k} / I_{1P} \qquad (2)$$

Here, I_{1k} is the zero-sequence current fundamental component of line k, I_{1P} is the sum of the zero sequence current fundamental components of all lines.

For the arc suppression coil grounding system, the arc suppression coil has little effect on the harmonic generation, so the FFT can be used to extract the fifth harmonic component from the zero sequence current as the fault feature. The fifth harmonic fault characteristic is calculated as follows:

$$X_3 = \varepsilon_{5k} / \varepsilon_{5p} \qquad (3)$$

Here, I_{5k} is the amplitude of the fifth harmonic component of line k, I_{1P} is the sum of the fifth harmonic components of all lines.

2.2. Improved Support Vector Machine Algorithm

In the resonant grounding system, the SVM classification idea is used to classify the special data at the time of failure into the trained model to obtain the line selection result.

Suppose there is a training sample set $\{x_i, y_i\}$, $i = 1,2,\ldots,n$, $y \in \{+1,-1\}$, Use the nonlinear mapping $\varphi(\cdot)$ to map the input sample data space to the high-dimensional feature space, and construct the optimal classification hyperplane in the high-dimensional feature space:

$$\begin{cases} f(x) = \omega \cdot \varphi(x) + b = 0 \\ y_i \cdot (\omega \cdot \varphi(x) + b) \geq 1 \end{cases} \qquad (4)$$

In the actual situation, the construction of the optimal hyperplane can be transformed into the following quadratic programming problem:

$$\begin{aligned} &\min \varphi(x) = \|\omega\|^2 / 2 + C\sum_{i=1}^{l} \zeta_i \alpha \\ &s.t.\ \ y_i \cdot (\omega \cdot \varphi(x) + b) \geq 1 - \zeta_i \end{aligned} \qquad (5)$$

Here, ω represents the weight vector, b represents the threshold, C indicates the penalty parameter for the error, $C > 0$, ζ_i is a slack term。Classification interval is $2 / \|\omega\|$, To maximize $2 / \|\omega\|$ is to minimize $\|\omega\|^2 / 2$.

The kernel function in the development of SVM algorithm is of great significance. There are generally three types: polynomial kernel function, RBF kernel function and neural network kernel function. Different kernel functions can generate different support vector classifiers. Here choose RBF kernel function $k(x,x') = \exp(-\|x,x'\| / 2\sigma^2)$, Because it is only necessary to determine an σ parameter in the RBF kernel function, which is beneficial to parameter optimization, the decision function of the optimal classification plane is

$$f(x) = \text{sgn}(\omega^* \cdot x + b^*) = \text{sgn}\left[\sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b\right] \tag{6}$$

Similarly, the nonlinear support vector machine constructs the optimal hyperplane can also be transformed into a quadratic programming problem. Further transformed into its dual quadratic programming problem

$$\begin{aligned} &\max L(\alpha) = \sum_{j=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_i K(x_i, x_j) \\ &s.t. \qquad 0 \le \alpha_i \le C, \sum_{j=1}^{l} y_i \alpha_i = 0, i = 1,2,\ldots,l \end{aligned} \tag{7}$$

2.3. Improved Particle Swarm Optimization

The particle swarm optimization algorithm calculates the fitness value through the fitness function in the optimization process, and compares it to continuously update the individual extremum (Pbest) and the group extremum (GBest). The speed and position are updated as follows:

$$\begin{aligned} v_{k,e}(t+1) = w(t)v_{k,e}(t) + c_1(t) \cdot r_1(t)(p_{k,e}(t) - x_{k,e}(t)) \\ + c_2(t) \cdot r_2(t)(p_{g,e}(t) - x_{k,e}(t)) \end{aligned} \tag{8}$$

$$x_{k,e}(t+1) = x_{k,e}(t) + v_{k,e}(t+1) \tag{9}$$

Here, t is the current number of iterations; $t_{\max}$ is the maximum number of iterations; $v_{k,e}$ is the k-th particle（$i = 1,2,\ldots, N$）velocity of the e-th particle of the kth particle（$e = 1,2,\cdots, E$）; $x_{k,e}$ is the particle position of the e-th dimension of the k-th particle; $p_{k,e}$ is the individual optimal position of the e-th dimension of the k-th particle; $p_{g,e}$ is the optimal position of the group in the e-th dimension; r_1、r_2 respectively represent two mutually independent uniformly distributed random numbers in the closed interval. $[0,1]$.

Improvements to traditional particle swarm optimization algorithms:

The inertia weight is of great significance to the PSO algorithm. The traditional PSO adopts a fixed weight, which is not conducive to the optimization of the particle. The requirement for the inertia weight should be: it is beneficial to traverse all the value intervals in the early stage of optimization, and it is conducive to algorithm convergence in the later stage of optimization. The improvement of inertia weight is as follows:

$$w = \frac{\sqrt{r_3}}{2} + (w_{end} - w_{start}) \cdot \frac{t_{\max} - t}{t_{\max}} \tag{10}$$

Here， w_{start}， w_{end} are the initial inertia weight and the termination inertia weight respectively; r_3 is a uniformly distributed random number in the closed interval $[0,1]$.

c_1, c_2 are acceleration factors, which represent the individual cognitive factors of the particles and the social cognitive factors, which represent the learning ability of the particles.Usually the acceleration factor is $c_1 = c_2 = 2$. In this paper, the acceleration factor is improved, so that the particle swarm particle has a strong global search ability in the early stage of optimization, and it is not easy to fall into the local optimal solution. In the later stage, it can search finely in the vicinity of the optimal solution to achieve the optimal solution:

$$c_1 = \frac{5}{\pi} + \frac{1}{10}\cos\left(\frac{\pi \cdot t}{t_{\max}}\right) \tag{11}$$

$$c_2 = \frac{9}{2\pi} - \frac{1}{10}\cos\left(\frac{\pi \cdot t}{t_{\max}}\right) \quad (12)$$

The cosine function is used to improve c_1、c_2 in above, so that the particle has a great probability to jump out of the local optimal solution. But there is great similarity between the particles in the late iteration. In order to increase the search range of particles, the genetic algorithm is used to further improve the particle swarm optimization algorithm. The specific expression is: In the particle iterative process, the selection and crossover are adopted, and the selection method of the tournament selection method in the genetic algorithm is selected.

2.4. Improve PSO-SVM Algorithm Flow

The main idea of using improved PSO-SVM for fault line selection is to use the improved PSO algorithm to optimize the SVM parameter pairs. The SVM uses the optimal parameters obtained for training, and then brings the sample data into the trained model. The result of the line selection is obtained. The improved PSO-SVM algorithm flow is shown in Table.1.

Table 1 Flow chart of fault line selection algorithm based on improved PSO-SVM

Step 1:Zero-sequence current processing by wavelet packet transform and fifth harmonic method, The transient energy component eigenvalues, the fundamental component eigenvalues and the fifth harmonic component eigenvalues are calculated from equations (1), (2), and (3), respectively.
Step 2: Calculate the particle fitness value according to formula (7). Cross-select according to the tournament selection method to generate a new set of particles.
Step 3: Update the optimal position of the individual particles and the optimal position of the group.
Step 4 according to the parameter improvement strategy (10) (11) (12), and updating the particle velocity and position based on equations (8) and (9) respectively.;
Step 5: If the termination condition of the optimal parameter optimization is satisfied, the parameter optimization is ended, Otherwise, return to step 2
Step 6: Training the SVM using the optimal parameters on the training set;
Step 7: The test set is input to the SVM model for fault line selection;Get the result of the line selection.

3. Results and Discussion

Taking the parameters of the 110kV side #2 section bus and its four feedback lines of a 110kV substation in Ningbo, Zhejiang Province as an example, the simulation model is built by matlab to simulate, and the simulation diagram is shown in Figure 1.

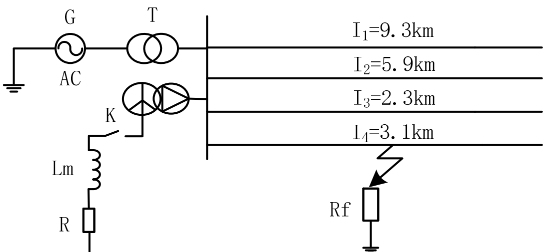

Fig.1 10KV distribution network of four feedback lines

In fig.1, G is an ideal power supply of 110kV, T is the main transformer, R_f is the fault point transition resistance, K、L_m、R are the control switches, inductors, and median resistors in the arc suppression coil assembly. Line L_1 is a pure overhead line with a length of l_1=9.3km;Line L_3 is a pure cable line with a length of l_3=6.3km;Line L_2,L_4 are overhead line-cable hybrid lines, each of which is $l_2 = 5.9\text{km}$, $l_4 = 7.1\text{km}$ .The empty line and cable line feeder parameters are shown in Table 2

Table 2 Line feeder parameters (km)

Feeder type	R_1/Ω	L_1/mH	$C_1/\mu\text{F}$
Overhead lines	0.178	1.20	0.0099
Cable	0.254	0.2337	0.3411
Feeder type	R_0/Ω	L_0/mH	$C_0/\mu\text{F}$
Overhead lines	0.24	5.3537	0.0079
Cable	2.68	1.0220	0.2668

In the table, R_1、L_1、C_1 are the positive sequence resistance, inductance, and capacitance on the line per kilometer, respectively; R_0、L_0、C_0 are the zero sequence resistance, inductance, and capacitance on the line per kilometer, and the sampling spectrum is set to 4000Hz .

The metal grounding resistance of the four lines is 10Ω、100Ω、150Ω、200Ω, the distance from the fault point to the busbar is 1km、2km、5km, and the zero-sequence current signals of each line are collected when the initial phase angle is 0°, 45°, and 90°. The zero-sequence current signals of each line are decomposed by the wavelet packet 4 layers, and the transient energy characteristics, steady-state fundamental component characteristics and fifth-order harmonic component characteristics of each line are extracted as the original data. 100 sets of training samples were taken from the original data, and 50 sets were taken as test samples.

The training samples are input into the improved PSO-SVM model for training, and the trained SVM is used to test the test samples, and the output can obtain the line selection result. The model input is 3D and the output is 1 or -1. "1" stands for non-faulty line and "-1" stands for faulty line.

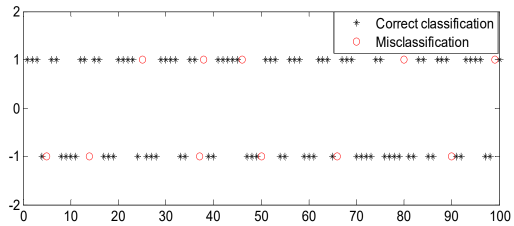

Fig. 2 (a) based on SVM algorithm resonant grounding system fault line selection results

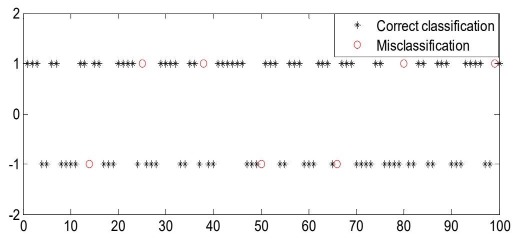

Fig.2(b) Results of fault line selection for resonant grounding system based on traditional PSO-SVM algorithm

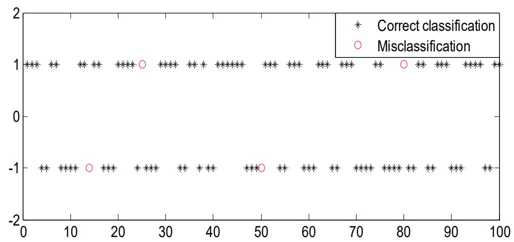

Fig.2(c) is based on the improved PSO-SVM algorithm for resonant grounding system fault line selection results.

Comparing the three methods in Figure2, it can be found that the improved PSO-SVM has the highest correct line selection rate. The specific data pairs are shown in Table 3.

Table 3 performance comparison of different line selection methods

Line selection method	C	σ	Operation hours	Accuracy
Traditional SVM	10.7782	0.0563	0.9203	0.8767
Traditional PSO-SVM	13.4659	0.9436	0.5838	0.9204
Improve PSO-SVM	17.6597	0.1433	0.6468	0.9589

It can be seen from Table 3 that the improved PSO-SVM line selection rate is the highest, but the line selection running time is slightly higher than the traditional PSO-SVM algorithm line selection running time, because the improvement of the traditional PSO algorithm refers to the genetic algorithm. Cross-selection operations add complexity but increase the likelihood that particles will jump out of the local best. In addition, although the improved PSO-SVM runs much longer than the traditional PSO algorithm, it is still in the acceptable range lower than the traditional SVM algorithm, and the improved PSO-SVM algorithm has the highest line selection accuracy. In summary, the improved PSO-SVM has the best performance for fault line selection of the resonant system.

4. Conclusions

An improved PSO-SVM intelligent line selection method is proposed for fault line selection of resonant system, which makes the particle group not easy to fall into the local best, combined with wavelet packet variation and fifth harmonic method, and common SVM line selection method and unmodified PSO. Compared with the SVM method, the correct line selection rate is the highest. Although some efficiency is sacrificed, it is still within the acceptable range. The improved PSO-SVM line selection method has the best comprehensive performance. In future research, the efficiency of line selection can be further optimized.

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