Single-phase-to-ground Fault Line Selection Method Based on STOA-SVM

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Abstract. In view of the complex characteristics of nonlinearity and non-stablility of the zero-order current of each line after the single-phase ground fault of the distribution network, a distribution network fault selection method based on Sooty Tern Optimization Algorithm(STOA) and the combination of support vector machine is proposed. At first, the zero-sequence current before and after fault is obtained, then five kinds of IMFs including different components are obtained by ensemble empirical mode decomposition, and the energy entropy of the fault transient zero-sequence current is obtained by Hilbert transform, the results of training and testing are obtained by inputting the feature vector. The simulation results show that the accuracy of the proposed line selection model is 97.5%.

Keywords: Sooty Tern Optimization Algorithm; Support Vector Machine; Single phase to ground fault; Ensemble Empirical Mode Decomposition.

1. Introduction
After the single-phase ground fault of china's low-voltage distribution network, due to the weak current, arc instability and influenced by random factors, the fault selection line problem has not been solved well. According to statistics, the low-voltage distribution network single-phase ground fault accounted for about 80% of the total number of faults[1]. When single-phase-to-ground fault occurs, the power system still maintains three-phase symmetry and can continue to operate with the fault for 1 ~ 2 hours, but the long-time operation with the fault will cause more harm to the power system, therefore, in order to ensure the safe and stable operation of the power system[2], it is necessary to find and remove the faults quickly when they occur.

At present, there are two methods of Fault Line Selection, passive method and active method. The passive method mainly uses steady state[3], transient, traveling wave and phase current[4-5]. The active line selection method mainly uses the disturbance quantity[6-7]. When small current grounding fault occurs, the transient information generated by the system is much larger than the steady information, and is not affected by the ARC suppression coil. Even if the fault occurs at the zero point of the phase voltage, its amplitude is still close to the steady power frequency component, the main methods of transient current selection are the first half wave method[8], the transient direction method[9] and the group transient current comparison method[10].

In this paper, the theoretical characteristics of steady state and transient state of zero-sequence current are analyzed and studied when single-phase-to-ground fault occurs in the system, on this basis, a new method of fault line selection based on Sooty Tern optimization Support vector machine is proposed.
Firstly, the ensemble empirical mode decomposition (EMD) is used to obtain the IMFs of each output line, and then the energy entropy of the fault transient zero sequence current is obtained by Hilbert transform, finally, the output line label is taken as the classification target, and the fault line is obtained by the output result. Thus, the problem of Fault Line Selection is successfully transformed into the problem of fault line classification, and the reliability and rapidity of fault line selection are improved.

2. Algorithmic Theory

2.1. Ensemble Empirical Mode Decomposition (EEMD)
Because of the abrupt disturbance and the mode aliasing in the transient signal processing of EMD algorithm, the intrinsic mode function component lost its physical meaning. The EEMD algorithm overcomes the mode confusion problem of EMD by adding different Additive white Gaussian noise and the average of multiple sets.

2.2. Sooty Tern Optimization Algorithm (STOA)
The Sooty Tern Optimization Algorithm was developed by G. DHIMAN and A. Kaur proposed a new optimization algorithm for industrial engineering problems in 2019, inspired by the natural foraging behavior of seabirds, Sooty Tern's omnivorous birds that feed on earthworms, insects, fish and other foods. This algorithm has strong global search ability and high precision.

2.2.1. Migration Behavior (global exploration)
The migration behavior, the exploration part, is mainly divided into three parts: Conflict Avoidance, aggregation and renewal.

- Conflict Avoidance:
  \[ c_{st} = S_A \times p_{st} | (Z) \]  (1)
  Where \( p_{st} \) stands for Sooty Tern's current position and \( c_{st} \) stands for position without colliding with other sooty terns, \( S_A \) stands for a collision avoidance variable to calculate the post collision position, its constraints are as follows: Formula (2).
  \[ S_A = C_f - (Z \times (C_f / \text{Max}_{\text{iterations}})) \]  (2)
  \[ Z = 0, 1, 2, ..., \text{Max}_{\text{iterations}} \]  (3)
  Where \( C_f \) is used to adjust the control variable for \( S_A \), \( Z \) represents the current number of iterations, so \( S_A \) decreases linearly from \( C_f \) to 0. The value of \( C_f \) in this article is set to 2, so \( S_A \) will decrease gradually from 2 to 0.

- Congregate:
  Aggregation is to approach to the best position in the neighboring tern without conflict, that is, to the position of the optimal solution. The mathematical expression is as follows:
  \[ m_{st} = C_B \times (p_{\text{best}} (Z) - p_{st} (Z)) \]  (4)
  Where \( m_{st} \) represents the process of moving from \( p_{st} \) at different locations to \( p_{\text{best}} \) at the optimal solution, \( C_B \) is a more comprehensive random variable to be explored:
  \[ C_B = 0.5 \times R_{and} \]  (5)
  Where \( R_{and} \) is a random number between 0 and 1.

- Updates:
  An update is a path that is updated in the direction of the optimal solution. The mathematical expression for this path is \( d_{st} \):
  \[ d_{st} = c_{st} + m_{st} \]  (6)
2.3. Support Vector Machine (SVM)

The basic idea of SVM: for Linear separable samples, the optimal classification plane is found in the original space; for linear unseparable problems, firstly, by means of nonlinear transformation $\Phi(.)$ the sample is transformed from the original input space to the linear separable problem of the high-dimensional characteristic space (Hilbert Space).

Let the sample set $(x_g, y_g)$, where $g = 1, 2, \ldots, L$, $y_g \in \{-1, 1\}$, then the optimal classification hyperplane is:

$$ W\phi(x_g) + b = 0 $$

At this point, the binary classification problem of the original input space can be expressed as:

$$ y_g (W\phi(x_g) + b) \geq 1 \quad g = 1, 2, \ldots, L $$

Introducing kernel function

$$ K(x_g, x) = \langle \Phi(x_g), \Phi(x) \rangle $$

According to the Kuhn-Tucker Theorem, $a_g$ is not 0, and the corresponding training sample is called the support vector and is denoted as $a_g^*$. The final optimal classification function expression is

$$ f(x) = \text{sgn} \left\{ \sum_{g=1}^{l} y_g a_g^* K(x_g, x) + b^* \right\} $$

In the formula, $l$ is the number of Support vector machine.

In this paper, we choose gauss Radial basis function, which is more commonly used:

$$ K(x_g, x) = \exp \left( -\frac{||x - x_g||^2}{2\sigma^2} \right) $$

3. Algorithmic Flow

The Algorithm is as follows:

- When the zero sequence voltage $U_0$ of the bus is greater than 0.3UN, the line selector is started, and the zero sequence current of the feeders before and after the fault is recorded.
- decomposition of zero-sequence current. Each outgoing zero-sequence current is decomposed by five layers of EEMD, and five modal components are obtained.
- The EEMD intrinsic mode component is selected to obtain the energy entropy, and the EEMD eigenvector $E = [ E_1, E_2, \ldots, E_i ]$ is constructed.
- Model Training and testing. According to the above flow, change the fault parameters, and get the zero sequence current under different fault conditions. After constructing the feature vector, half of the data are input to the training set STOA-SVM for learning, and the other half are used as the test sample set, verify the effectiveness of line selection.

![Fault Line Selection for small current single-phase-to-ground fault based on EEMD energy entropy and SVM.](image)
4. Simulation Example

4.1. Model Building
A 110kv/10.5 Kv low current grounding distribution network model with 4 feeders is built in PSCAD, as shown in figure 2.

![Distribution Network simulation model](image)

Three-phase power supply adopts infinite power model, rated capacity is 300 MV·A, transformer capacity is 31.5 MV·A, using Y/Δ wiring, arc suppression coil using over-compensation, and $\theta = 8$. Since the length of distribution line is generally short, the equivalent model of transmission line is selected in this paper, and the length of each line is 15km, 10km, 18km and 6km respectively.

| Line type       | Parameters | Overhead line | Cable Wire |
|-----------------|------------|---------------|------------|
| Overhead line   | R1/Ω       | 0.175         | 0.27       |
|                 | L1/mH      | 1.21          | 0.354      |
|                 | C1/μF      | 0.0097        | 0.3391     |
|                 | R0/Ω       | 0.23          | 2.7        |
|                 | L0/mH      | 5.478         | 1.109      |
|                 | C0/μF      | 0.008         | 0.28       |

Table 1. Data setting.

The simulation parameters are set as follows: sampling frequency is 10000Hz, simulation time is 0.3 s, fault time is 0.05 s, fault duration is 0.1 s.

4.2. Simulation Example
When the fault closing angle of T1 line is 0°, the fault resistance is 0.01, and the single-phase-to-ground fault occurs at 1.46 km from the first end of T2 line, the line selection device is started, the zero sequence current curve of T1 T2 T3 T4 is obtained as shown.
According to the above theoretical analysis, the fault zero sequence current is mainly composed of decaying DC component, power frequency AC component and high frequency oscillation component. In order to decompose the signal better, this paper adopts the method of EEMD to decompose the signal, and finally obtains 5 modal components which are consistent with the components of theoretical analysis.
4.3. Batch Testing
According to the simulation model in section 4.1, the ground resistance is simulated to be 10, 100, 200, 250, 400 and 500, and the initial failure angle is 0°, 30°, 45°, 60°, 90° and 120°. The total number of samples is 720 under the condition of 4 feeders in 5 different positions, and the zero-sequence current value is transformed by EEMD, then the feature vector is extracted. Using the STOA-SVM, based on the above sample set, the first classification result is the outline 1 fault, and so on, a total of four classification results. According to the test result of figure 11, the correct rate of SVM is 97.5%.

5. Conclusion
This paper presents a Support vector machine fault line selection model (STOA-SVM) based on Sooty Tern Algorithm optimization. In this paper, the model of 4 feeders small current grounding system is established, and various fault conditions are simulated, the zero sequence current signal is obtained and the feature vector is extracted, the trained STOA-SVM classifier can still be recognized effectively. Under the STOA-SVM model training and testing, the method proposed in this paper achieves a high accuracy rate of line selection. In the future, more machine learning algorithms will be
used to solve the problem of fault line selection in power system, which can improve the automation degree of distribution network protection. Although the method proposed in this paper has achieved good results in the model, there are still some deficiencies in the parameter determination of Sooty Tern's optimization, and the optimum parameters which are more suitable for the decomposition of zero sequence current need to be studied. At the same time, there are many influencing factors in the actual distribution network. Whether the method proposed in this paper can ensure the accuracy needs further verification.

Acknowledgments
Project Supported by Science and Technology Project of State Grid Sichuan Electric Power Company (Contract No.521997180016).

References
[1] Xu Yanchun, Zhao Caicai, Sun Sihan, Mi Lu. Active Distribution Network fault location method based on improved LMD and energy relative entropy. CLP Power China: 1-11[2021-08-28].
[2] Liu Yongsheng, Chen Jun, Li Juan, Hou Wei, Li junting, Xu Qingshan. Current transient based distributed protection scheme for DC distribution network [J]. Power System Automation, 2021,45(05): 159-167.
[3] Zhang Lei. Study on single-phase-to-ground fault line selection strategy in distribution network [j]. Power Equipment Management, 2020(06): 59-60.
[4] Lin Jianxiong. Study on traveling wave fault location technology for single-phase-to-ground fault in complex distribution network [D]. North China Electric Power University, Beijing, 2018.
[5] Chow hing-chung. Study on fault location in distribution network based on traveling wave modulus transmission time difference [D]. Changsha University of Science and Technology, 2015.
[6] Xia Bing. Study on the Oscillation Mechanism of distribution network and its suppression. Shandong University, 2019.
[7] Chiao jin-young. Power Quality Problem Analysis and disturbance detection of DC distribution network [D]. Yanshan University, 2017.
[8] Zhou Jun, Liu Na, Li Shuguang. Equivalent half-wave injection method for fault line detection in non-effectively grounded system. Electrical measurement and instrumentation, 2020,57(04): 55-60.
[9] Liu Minpei, Lin Jingyan, Hong Weibin, Huang Chaoyi, Lin Wengui, Wu Rongfu. SUMMARY OF SINGLE-PHASE-TO-GROUND FAULT transient location techniques in medium-voltage distribution networks [j]. Electrical switches, 2019,57(04): 1-4.
[10] Miao Youzhong. Study on integral transient protection and distributed intelligent fault location of feeder in distribution system [d]. Tianjin University, 2004.