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AN IDENTIFICATION METHOD FOR VOLTAGE SAG IN DISTRIBUTION SYSTEMS USING SVM WITH GREY WOLF ALGORITHM

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Abstract

For the voltage sag caused by short-circuit fault, transformer switching and induction motor starting in distribution network, an optimised support vector machine (SVM) method based on Grey Wolf algorithm (GWO) is proposed for voltage sag identification. The empirical mode decomposition method is used to analyse the voltage sag signal, obtain an inherent mode function set (IMFs), and calculate the energy entropy of each order IMF as the eigenvector. In order to solve the problem that the traditional SVM is easy to fall into local optimisation in the process of optimisation, a method of optimising the penalty factor and kernel function parameters of SVM through GWO is proposed, a GWO-SVM classifier is constructed, and then the extracted feature vector is input into the GWO-SVM classifier to train and recognise the samples, so as to realise the automatic classification and identification of different types of voltage sag sources. The simulation results show the effectiveness of the extracted feature vector and GWO-SVM classifier. Compared with other five traditional methods, it is verified that it has fast speed and high precision.

Key Words

Distribution systems; Voltage sag source identification; Gray Wolf algorithm; Support vector machine; Empirical mode decomposition

1. Introduction

In recent years, with the continuous increase of modern power electronic equipment and sensitive load in China, the industrial process of precision instrument manufacturing has higher and higher requirements for power quality. Fast and accurate identification of voltage sag source is conducive to the prevention and treatment of voltage sag and ensure power quality [1]. In real life, the occurrence of voltage sag is inevitable and its harm is huge. More than 70% of power quality problems in power system are caused by voltage sag [2]. In order to prevent and effectively control voltage sag, how to quickly and accurately judge the possible type of voltage sag source is the key.

For the identification of voltage sag disturbance sources, most traditional methods use the characteristics and data of different voltage sag sources and adopt the manual identification method, which has the advantages of simplicity, convenience, efficiency, and intuition, but it is not conducive to the identification of large sample machines [3], [4]. Some studies have proposed an S-transform to analyse the change of voltage sag signal amplitude, extract six transformed characteristic indexes, use the multifractal spectrum parameter generalised Hurst index to improve the accuracy of classification and identification in the noise environment, input the extracted characteristic indexes into the support vector machine (SVM), and train various voltage sag source types, So as to realise the classification and identification of different voltage sag sources, but the time window of S-transform is fixed, which is difficult to be applied in practical engineering [5]. Other scholars use adaptive S-transform to analyse the sag signal, construct S-transform modulus matrix, decompose the sag signal into different time-frequency subspaces, extract six feature quantities and input them into the SVM optimised by particle swarm optimisation for classification. However, only three voltage sag sources are mentioned in this work, so this method is not universal and applicable [6].

In some studies, BP neural network is used as the basic classifier, which has the disadvantages of poor recognition effect of single classifier and strong pertinence of sample selection. AdaBoost ensemble learning algorithm is introduced to integrate several basic classifier BP neural networks into strong classifier BP AdaBoost network to accurately identify the type of voltage sag source, However, in the process of solving, BP neural network requires high training samples and long training time, which is easy to fall into local optimisation [7]. Some other studies extract the time-domain features of voltage sag signals, extract the two time-domain features of energy entropy and singular entropy by S-transform, and construct the 42 dimensional

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recognition feature vector, so as to realise the identification of voltage sag sources. Because the new algorithm of limit learning machine of single hidden layer feedforward neural network is used in calculation. There will be defects of huge amount of calculation and long calculation time [8]. Considering the disadvantages of long classification time and low accuracy of traditional voltage sag source identification methods, some scholars propose a method to extract the characteristic quantities, such as voltage sag start and end time, sag degree and phase jump by using the modular time-frequency matrix of generalised S-transform, and then use the genetic algorithm to optimise the input weight and hidden layer threshold of elm to construct a GA-ELM classifier. Then the voltage sag source is effectively identified [9].

In view of the possibility of misjudgement caused by manually obtaining characteristics, some scholars propose a voltage sag source identification method based on deep learning model fusion, which obtains the temporal and spatial characteristics of voltage sag signal through convolution neural network in deep learning algorithm. The deep confidence network is used to replace the full connection layer used to purify high-dimensional features and act as a classifier in the convolutional neural network, so as to enhance the multi-label classification ability of the network and improve the accuracy of voltage sag source identification [10]; In order to overcome the difficulty of feature extraction, some scholars first use the waveform variation characteristics of voltage sag RMS, use coarse-grained RMS data to construct the population corresponding to short-circuit fault, large capacity induction motor startup and transformer switching, use training samples for learning, and use Markov distance to construct discriminant function and criteria. The input test samples are judged to realise the identification of voltage sag source, but this method is only suitable for a single voltage sag source with small samples, which has great limitations for practical engineering application [11].

Based on the previous research on SVM classification [6], [12]–[15], aiming at the problem that the traditional SVM is easy to fall into local optimisation in the optimisation process, this paper proposes a method to optimise the penalty factor and kernel function parameters of SVM through gray wolf algorithm (GWO), and construct GWO–SVM classifier, Then the extracted feature vector is input into GWO–SVM classifier to train and identify the samples, so as to realise the automatic classification and identification of different types of voltage sag sources.

2. SVM classifier optimised by GWO

2.1 SVM classifier

Let the sample data (x_i, y_i), $1 \le x \le n$, $x \in R^d$ and $y \in \{-1, 1\}$ be classification labels. By constructing the classification hyperplane $w^T x + b = 0$and the classification function $g(x) = w^T x + b$, the classification interval between the two types of samples is maximised. $\lambda = y\left(w^T x + b\right)$ is defined as the functional interval between the eigenvector and the hyperplane. In order to construct the optimal classification hyperplane, the geometric distance between the data points and the hyperplane is defined as:

$$\lambda = \frac{y\left(w^T x + b\right)}{\|w\|} \tag{1}$$

When the samples are classified and identified, the larger the geometric interval between the two types of samples, the more conducive to classification. Assuming that all samples meet $|g(x)| = \left|w^T x + b\right| \ge 1$, the geometric interval between the two types of samples is $2/\|w\|$, which can maximise the function interval between the two types of samples, that is, find the minimum value of $\|w\|^2/2$. Therefore, constructing the optimal classification hyperplane problem satisfying the maximum geometric interval is equivalent to solving the optimal solution of the following constrained optimisation problem:

$$\begin{cases} \min \frac{\|w\|^2}{2} \\ \text{s.t.} \;\; y_i\left(w^T x_i + b\right) \ge 1, \quad \mathrm{i} = 1, 2, \ldots, n \end{cases} \tag{2}$$

In order to solve the convex optimisation problem of the above formula, an augmented Lagrange function is constructed:

$$L(w, b, \delta) = \frac{\|w\|^2}{2} - \sum_{i=1}^{n} \delta_i \left[y_i\left(w^T x_i + b\right) - 1\right] \tag{3}$$

To minimise L for w and b, find the partial derivatives of w and b, respectively, and make them equal to 0 to obtain:

$$\begin{cases} w = \sum_{i=1}^{n} \delta_i y_i x_i \\ \sum_{i=1}^{n} \delta_i y_i = 0 \end{cases} \tag{4}$$

The Lagrange function can be obtained by substituting it into the above formula, which contains only one variable:

$$L(w, b, \delta) = \sum_{i=1}^{n} \delta_i - \frac{1}{2} \sum_{i,j=1}^{n} \delta_i \delta_j y_i y_j x_i^T x_j \tag{5}$$

Finding the maximum of δ becomes the problem of optimising the dual variable δ, which is obtained from the above formula:

$$\begin{cases} \max_\delta \sum_{i=1}^{n} \delta_i - \frac{1}{2} \sum_{i,j=1}^{n} \delta_i \delta_j y_i y_j x_i^T x_j \\ \text{s.t.} \;\; \delta_i \ge 0, \quad \mathrm{i} = 1, 2, \ldots, n \\ \sum_{i=1}^{n} \delta_{ij} y_i = 0 \end{cases} \tag{6}$$

If δ' is the optimal solution, then:

$$f(x) = \operatorname{sign}\left[\sum_{i=1}^{n} {\delta'}_i y_i (x_i, x) + b'\right] \tag{7}$$

where δ' is the classification threshold.

In order to avoid too high dimension in the mapping process, the kernel function is used to replace the inner product, and the high-dimensional mapping process of eigenvector is changed from explicit to implicit, so that the inner product can be calculated in the original space, which is the kernel function method. Thus, the vector classification function of the optimal feature index becomes:

$$f(x) = \operatorname{sign}\left[\sum_{i=1}^{n} \delta'_i y_i K(x_i, x) + b'\right] \tag{8}$$

Some eigenvectors are disturbed by noise, and there will be outliers when they are mapped to high-dimensional space. Therefore, relaxation variable $\eta_i$and penalty factor $Q$are usually introduced to deal with outliers. The objective function becomes:

$$\begin{cases} \varphi(w, \eta) = \min \frac{\|w\|^2}{2} + Q\left(\sum\limits_{i=1}^{n} \eta_i\right) \\ \text{s.t. } \ y_i\left(w^T x_i + b\right) \geq 1 - \eta_i, \quad \mathrm{i} = 1, 2, \ldots, n \end{cases} \tag{9}$$

In general, the identification of voltage sag disturbance sources usually needs to classify many classes. Therefore, it is necessary to construct multi-level SVM and realise multi-level two classification through topology recognition framework, so as to multi-classify voltage sag sources. Because the extracted multi-dimensional voltage sag feature is usually linear and inseparable, by mapping the feature vector to the high-dimensional space, the various feature vectors of the voltage sag source can be linearly distinguished, and the voltage sag source can be distinguished by mapping them to the higher-dimensional feature space by using the kernel function. The kernel function uses an implicit mapping method to ensure that the inner product is carried out in the original space, so that this nonlinear expansion does not increase much computation. Kernel function can choose different parameters according to different practical problems and data, which is equivalent to constructing different kernel functions to meet different classification requirements.

In this paper, the commonly used radial basis kernel function is selected as the mapping function, and its expression is as follows:

$$K(x_i, x) = \exp(-\gamma ||x_i - x||^2) \tag{10}$$

2.2 Classifier Optimisation of SVM

Because the final classification result of SVM is largely affected by the penalty factor and the parameters in the kernel function, the GWO is used to optimise these two parameters in this paper, so as to improve the accuracy of classification and recognition.

When using SVM to deal with linear nonseparable problems, the setting of its parameters usually directly affects the classification performance of SVM. There are two kinds of parameters that have a great impact on the classification effect of SVM. One is the penalty factor and the other is the parameter in the kernel function. In this paper, the GWO will be used to optimise the selection of these two parameters. By optimising the value of the parameters, the flexibility of the kernel function mapping process and the recognition accuracy will be improved.

The GWO is used to optimise the parameters of SVM. The steps of the algorithm are as follows:

1. The voltage sag signal is decomposed by empirical mode decomposition (EMD) to obtain an inherent mode function set (IMFs), and then the energy entropy of each order IMF is calculated as the feature vector to construct the feature data set.
2. Establish the training set and test set.
3. Initialise the gray wolf number N, solution set dimension D, maximum iteration number t, gray wolf population $S = (S_1, S_2, \ldots, S_N)$ and gray wolf individual position $S_i = (s_{i1}, s_{i2}, \ldots, s_{\mathrm{iD}})$ in the gray wolf population, where $i \in \{1, 2, 3, \ldots, N\}$.
4. Traverse the gray wolf population, calculate the fitness value f_i of each individual, and record the positions of the top three gray wolf individuals as S_α, S_β and S_λ in turn.
5. Calculate the distance between each wolf ξ and α, β and λwolves, respectively, according to the following formula:

$$\begin{cases} D_\alpha = |C_1 S_\alpha(t) - S(t)| \\ D_\beta = |C_2 S_\beta(t) - S(t)| \\ D_\lambda = |C_3 S_\lambda(t) - S(t)| \end{cases} \tag{11}$$

   where D_α, D_β and $D_\lambda$are the distances between α, β and λ wolves and individuals of other wolves, respectively, and update the location of α, β, and λ wolves and prey according to the following two formulas:

$$\begin{cases} S_1 = S_\alpha(t) - K_1 D_\alpha \\ S_2 = S_\beta(t) - K_2 D_\beta \\ S_3 = S_\lambda(t) - K_3 D_\lambda \end{cases} \tag{12}$$

$$S_p(t+1) = \frac{S_1 + S_2 + S_3}{3} \tag{13}$$

   where $S_p(t+1)$ represents the location of prey (optimal solution).
6. Update the values of parameters a, K, and Q in the algorithm.
7. Judge whether the maximum number of iterations t is reached. If so, retain the optimal combination optimisation solution S_α, otherwise return to step 4).
8. The GWO optimized SVM classifier can be obtained from the above steps.

3. Voltage Sag Signal Characteristics and Decomposition

Using EMD method, the voltage sag signal is decomposed to obtain a series of intrinsic mode functions IMF. The IMF component must meet the following conditions:

1) At any time point, the average value of the envelope formed by the local maximum point and the envelope formed by the local minimum point is 0;

2) The number of extreme points and the number of zero crossings are the same or differ by 1 at most. Any signal satisfying the above conditions can be decomposed into a finite sum of IMF components.

After EMD of various voltage sag waveforms, each IMF component meets the above two constraints.

The EMD process of voltage sag signal is as follows:

1) Find out all extreme points of the voltage sag signal $f(t)$, and use spline function to fit the upper and lower envelope $n_1(t)$of voltage sag signal, respectively; The mean value of the upper and lower envelope is obtained, and the mean envelope is obtained. The signal $f(t)$ is subtracted from the mean value $n_1(t)$to obtain a new time series $q_1(t)$:

$$q_1(t) = f(t) - n_1(t) \tag{14}$$

If $q_1(t)$ meets the above two conditions of IMF, $q_1(t)$ is the first-order IMF component of voltage sag signal $f(t)$.

2) Generally, the time series cannot be a stable data series $q_1(t)$, so the above decomposition steps should be repeated. Repeat the above process i times until the obtained mean envelope approaches 0. The first IMF component obtained is recorded as $x_1(t)$, and $x_1(t)$ is also the highest frequency component obtained by EMD.

$$q_{1i}(t) = q_{1(i-1)}(t) - n_{1i}(t) \tag{15}$$
$$q_{1i}(t) = x_1(t) \tag{16}$$

3) The high-frequency component $x_1(t)$ is separated from the voltage sag signal $f(t)$ to obtain a new time series $w_1(t) = f(t) - x_1(t)$. Taking $w_1(t)$ as a new time series, repeat the above operations to obtain $x_1(t), x_2(t), x_3(t), \ldots, x_n(t)$, respectively.

$$\begin{cases} w_2(t) = w_1(t) - x_2(t) \\ w_n(t) = w_{n-1}(t) - x_n(t) \end{cases} \tag{17}$$

When $w_n(t)$ is a monotone function, the decomposition process terminates. At this time, the voltage sag signal can be expressed by the following formula:

$$f(t) = \sum_{k=1}^{n} x_i(t) + w_n(t) \tag{18}$$

where: $x_1(t), x_2(t), x_3(t), \ldots, x_n(t)$ is a series of IMFs obtained by the decomposition of voltage sag signal BB, representing the frequency components of voltage sag signal in different frequency bands, changing from high frequency to low frequency, accurately highlighting the local characteristics of the signal. $w_n(t)$ is a residual function, representing the change trend of voltage sag signal.

4. Feature Extraction Method for Voltage Sag

When voltage sag occurs in power system, the energy of voltage sag signal caused by each voltage sag source will change with different frequency distribution. After EMD decomposition, the voltage sag signal can be decomposed into a series of stable IMF components. After calculating the energy entropy of each order IMF component, a group of EMD energy entropy representing the voltage sag signal can be obtained, which can truly reflect the characteristics of the voltage sag signal. The characteristics of the original signal $f(t)$ can be described by these IMF energy entropy values, so the energy entropy of the IMF component can be extracted to construct the characteristic vector of the voltage sag signal [8].

In this paper, "one against rest" LIBSVM is used to identify the voltage sag source [15]. In this paper, test sample M1 is the data from single-phase grounding short-circuit fault, M2 is the data from two-phase short-circuit fault, M3 is the data from three-phase short-circuit fault, M4 is the data from the operation of transformer, and M5 is the data from the start-up of induction motor. For the voltage sag formed by M1 $\sim$ M5, five two classifiers of SVM are constructed, which are divided into SVM1 $\sim$ SVM5. During sample training, the nth sample in the nth bi-classifier is $+1$ and the rest is -1. In the sample test, the eigenvector of the test data sample is first input into SVM1. If the data of the test sample is 0, it will output $+1$. It can be judged that the disturbance source of voltage sag is single-phase grounding short-circuit fault, and the test is completed. Otherwise, the feature data is automatically input into SVM2, and so on until SVM5. Using this work, five typical voltage sag sources can be effectively identified.

The steps of voltage sag source identification based on EMD-SVM are as follows:

1) All kinds of voltage sag signals of three phases A, B, and C are decomposed by EMD to obtain each IMF signal.
2) After EMD decomposition, n IMF components are obtained, which is $W_1, W_2, W_3, \ldots, W_n$, respectively. The energy value of each IMF component is calculated to obtain the energy distribution characteristics of voltage sag signal in frequency domain, namely, $E = \{E_1, E_2, E_3, \ldots, E_n\}$. Ignoring the influence of residual quantity, the calculated energy distribution obeys the law of energy conservation.
3) Calculate the energy of each IMF signal according to the following formula:

$$E_i = \sum_{k=1}^{n} |f(t)|^2, (i = 1, 2, \ldots, n) \tag{19}$$

4) Calculate the total energy of each IMF signal:

$$E_{\text{all}} = (\sum_{k=1}^{n} |E_i|^2)^{1/2}, (i = 1, 2, \ldots, n) \tag{20}$$

5) Normalisation of each IMF signal energy:

$$E = [E_1/E_{\text{all}}, E_2/E_{\text{all}}, \ldots, E_n/E_{\text{all}}] \tag{21}$$

6) Calculate the energy entropy of each IMF and construct the eigenvector:

$$H = -\sum_{i=1}^{n} p_i log(p_i) \tag{22}$$

where $p_i = E_i/E_{\text{all}}$.

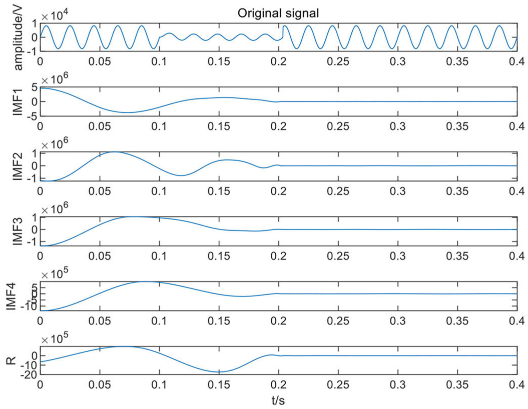


Figure 1. The EMD decomposition diagram of phase A voltage.

7) The feature vector constructed by the calculated energy entropy of each order IMF is input into the GWO–SVM classifier to train and test the samples.

5. Studying Cases

5.1 Data Acquisition

Based on MATLAB//Simulink, the simulation models of five common voltage sag sources, such as single-phase grounding short-circuit fault, two-phase short-circuit fault, three-phase short-circuit fault, transformer operation, and induction motor start-up are built and tested.

The sample data of different voltage sag sources can be obtained in the following ways:

1) For short-circuit fault, change the time of short-circuit fault and the size of line load;
2) For the operation of the transformer, change the connection mode of the primary and secondary windings of the transformer, the capacity of the transformer, the operation time of the transformer, and the size of the line load;
3) For the starting of induction motor, change the capacity of induction motor, the type of motor, and the starting time of motor.

Through the above simulation methods, 50 groups of sample data of each of the five typical voltage sag types can be obtained, of which 20 groups of each voltage sag type are used as the training samples of GWO–SVM classifier and the other 30 groups of data are used as the test samples.

5.2 EMD Decomposition and Eigenvalue of IMF Signal

(1) IMF eigenvalue of single-phase grounding short-circuit fault

The EMD decomposition diagram of phase a voltage in single-phase grounding short-circuit fault is shown in Fig. 1. As can be seen from Fig. 1, the original signal can be decomposed into four single component IMF and one residual function by the EMD method. The residual function represents the change trend of the signal rather than the component of the signal. As shown in Fig. 2,

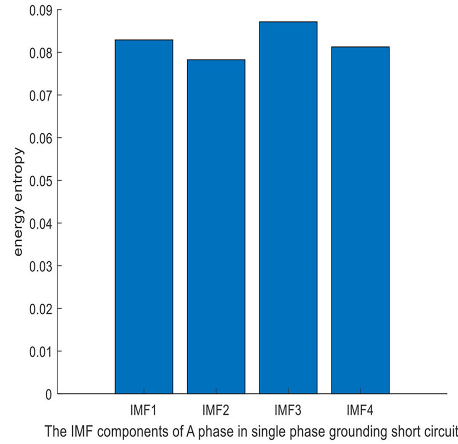


Figure 2. Energy entropy of A-phase due to single-phase grounding in single-phase grounding short-circuit fault short-circuit fault.

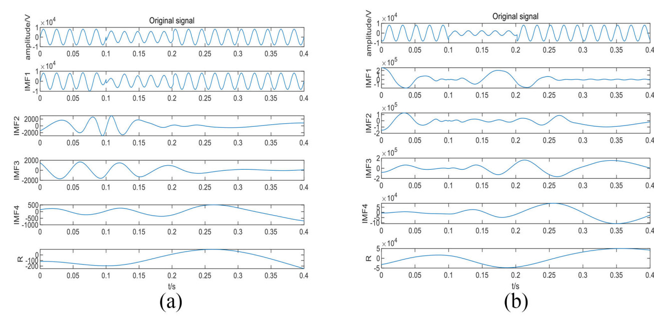


Figure 3. The EMD decomposition diagram of phases A and B voltage in two-phase grounding short-circuit fault: (a) Phase A and (b) Phase B.

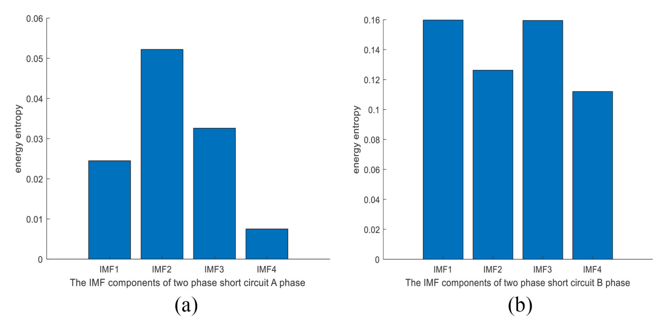


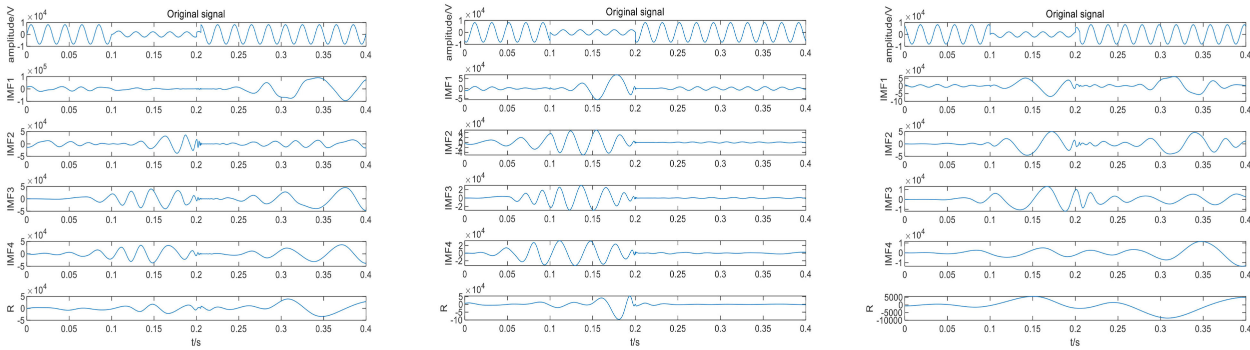
Figure 4. IMF eigenvalue of phases A and B due to two-phase grounding short-circuit fault: (a) phase A and (b) phase B.

IMF eigenvalue of phase A due to single-phase grounding short-circuit fault shows that the energy entropy contained in IMF3 is the highest, followed by IMF1, and then to IMF4, at least IMF2. These characteristics can be different from other voltage sag sources.

(2) IMF eigenvalue of two-phase short circuit fault

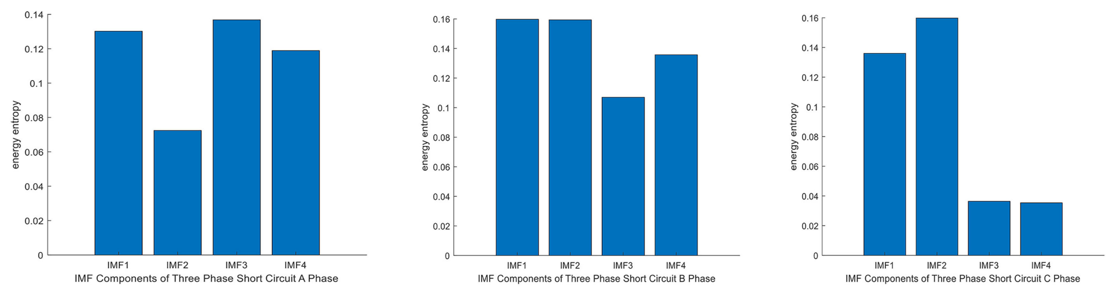
The EMD decomposition diagrams of phase A voltage and phase B voltage in two-phase short-circuit fault are shown in Fig. 3.

It can be seen from Figs. 3 and 4 that the original signal can be decomposed into four single component IMF



(a) (b) (c)

Figure 5. The EMD decomposition diagram of phase A and B voltage in three-phase grounding short-circuit fault: (a) phase A; (b) phase B; and (c) phase C.



(a) (b) (c)

Figure 6. IMF eigenvalue of phase A and B due to three-phase grounding short-circuit fault: (a) phase A; (b) phase B; and (c) phase C.

and one residual function, which represents the change trend of the signal rather than the component of the signal. In two-phase short-circuit fault, the energy entropy of each order IMF of phase A and phase B is shown in Fig. 4. Among the energy entropy values of each order IMF of phase A, the energy entropy contained in IMF2 is the highest, followed by IMF3, and then to IMF1, at least IMF4; Among the energy entropy values of each order IMF of phase B, the energy entropy contained in IMF1 and IMF3 is almost high, followed by IMF2, at least IMF4. These characteristics can be different from other voltage sag sources.

(3) IMF eigenvalue of three-phase short circuit fault
The EMD decomposition diagram of phase A, B, and C voltage in three-phase short circuit fault is shown in Fig. 5.

As can be seen from Fig. 5, the original signal can be decomposed into four single component IMF and one residual function by the EMD method. In three-phase short-circuit fault, there is obvious difference in the energy entropy of each order IMF of phase A, phase B and phase C, as shown in Fig. 6: in the energy entropy value of each order IMF of phase A, the energy entropy contained in IMF1 and IMF3 is almost high, followed by IMF4, at least IMF2; Among the energy entropy values of each order of IMF in phase B, the energy entropy contained in IMF1 and IMF2 is almost high, followed by IMF4, at least IMF3; Among the energy entropy values of each order of IMF in phase C, the energy entropy contained in IMF2 is the highest, followed by IMF1, and IMF3 and IMF4 are almost high.

(4) IMF eigenvalue of transformer switching
The EMD decomposition diagram of phase A, phase B and phase C voltage during transformer switching operation is shown in Fig. 7. As can be seen from Fig. 7, the original signal can be decomposed into four single-component IMF and one residual function by EMD method. The residual function represents the change trend of the signal. The energy entropy of each order of IMF of phase A, phase B and phase C voltage is different, and the difference is very obvious, as shown in Fig. 8. In Fig. 8, among the energy entropy values of each order of IMF in phase A, the energy entropy contained in IMF1, IMF2 and IMF4 is almost high, at least IMF3; Among the energy entropy values of each order of IMF in phase B, the energy entropy contained in IMF1, IMF2 and IMF4 is almost high, at least IMF3; Among the energy entropy values of each order of IMF in phase C, the energy entropy contained in IMF3 is the highest, followed by IMF2, and then to IMF4, at least IMF1.

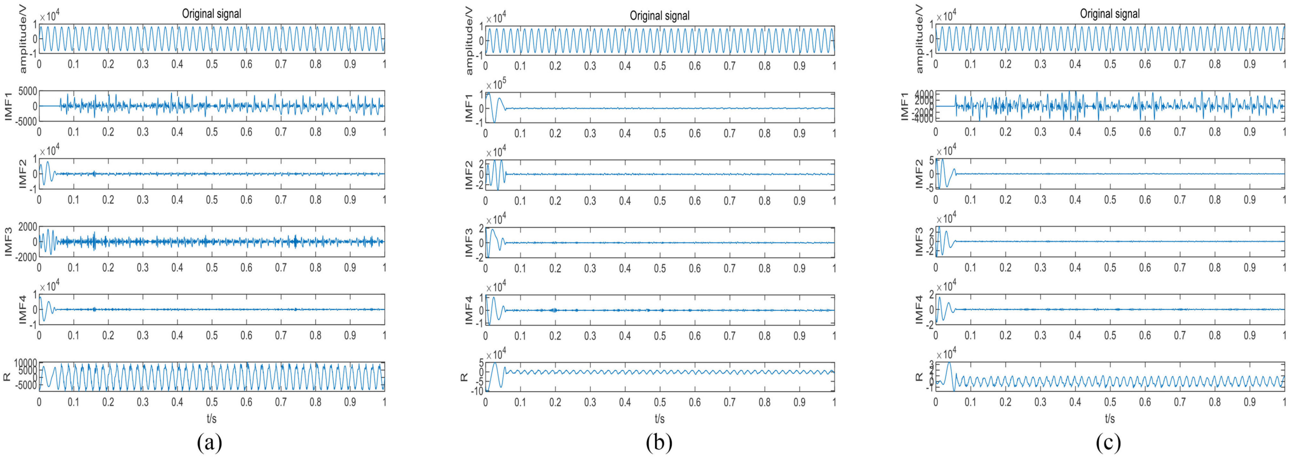


Figure 7. The EMD decomposition diagram of phase A and B voltage during transformer switching operation: (a) phase A, (b) phase B, and (c) phase C.

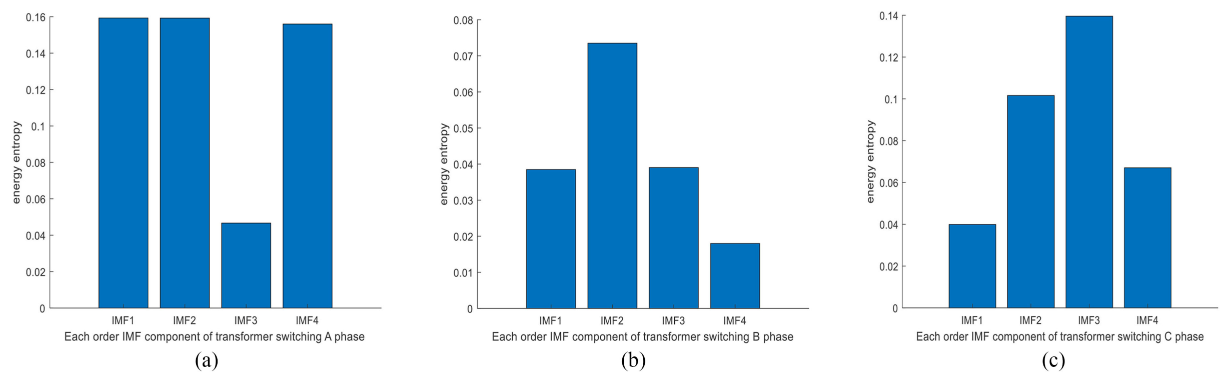


Figure 8. IMF eigenvalue of phase A and B due to transformer switching operation: (a) phase A, (b) phase B; and (c) phase C.

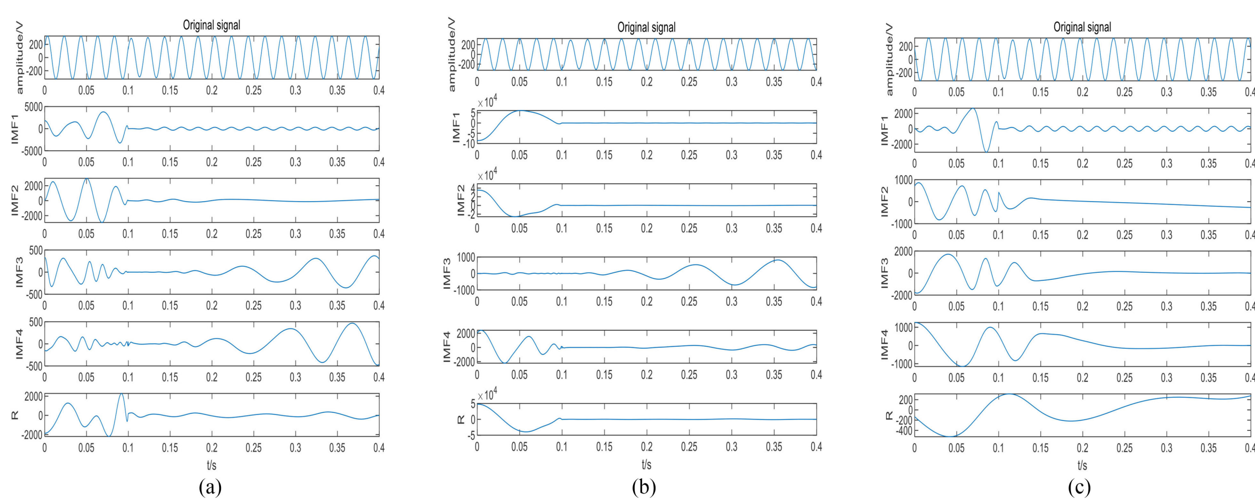


Figure 9. The EMD decomposition diagram of phase A and B voltage in induction motor start: (a) phase A, (b) phase B; and (c) phase C.

(5) IMF eigenvalue of induction motor start

The EMD decomposition diagram of phase A, phase B and phase C voltage during induction motor startup is shown in Fig. 9. It can be seen from Fig. 9 that the original signal can be decomposed into four single-component IMF and one residual function by EMD method. The residual

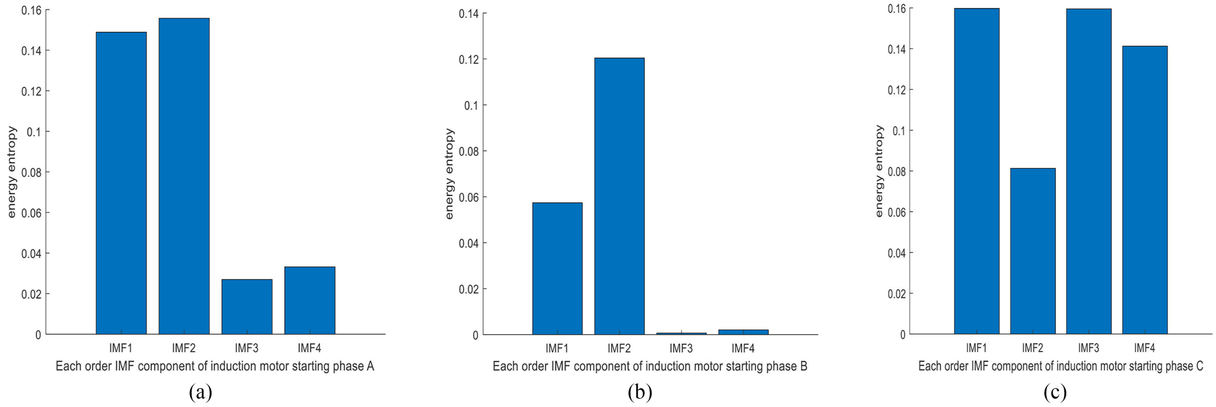


Figure 10. IMF eigenvalue of phase A and B due to induction motor start: (a) phase A, (b) phase B; and (c) phase C.

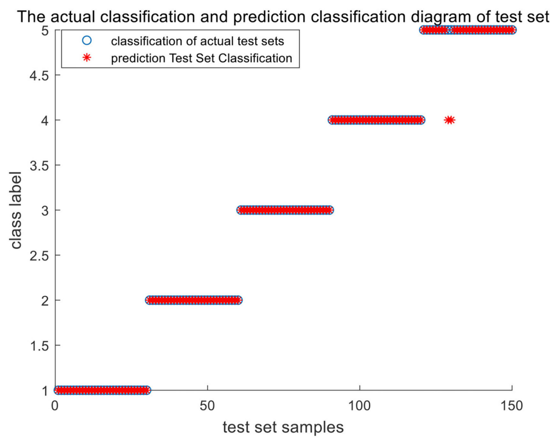


Figure 11. Voltage sag source identification based on GWO-SVM.

function represents the change trend of the signal, and the energy entropy of each order IMF of phase A, phase B and phase C is obviously different, as shown in Fig. 10. Among the energy entropy values of each order of IMF in phase A, the energy entropy contained in IMF2 is the highest, followed by IMF1, and then to IMF4, at least IMF3; Among the energy entropy values of each order of IMF in phase B, the energy entropy contained in IMF2 is the highest, followed by IMF1, and the energy entropy contained in IMF4 and IMF3 are very few; Among the energy entropy values of each order of IMF in phase C, the energy entropy contained in IMF1 and IMF3 is almost high, followed by IMF4, at least IMF2.

5.3 Voltage Sag Source Identification

In this paper, EMD is used to decompose the signal to obtain a series of intrinsic mode functions IMF, and then the energy entropy of IMF is calculated and normalized. The GWO is used to optimise the penalty factor Q of SVM and the parameters in the kernel function. The optimal value results are shown in Table 1.

Based on the classification and identification of five different voltage sag sources: single-phase grounding short circuit, two-phase short circuit, three-phase short circuit, induction motor startup and transformer switching

Table 1
Optimal Parameter Selection of SVM Based on GWO

Classifier	Penalty Factor Q	Kernel Function Parameters$^{\gamma}$
GWO-SVM	3.06444	0.920618

Table 2
Recognition Accuracy Based on GWO-SVM Classifier

Voltage Sag Type	Test Sample Size	Correct Identification Quantity	Correct Identification Rate
Single phase to ground short circuit	30	30	100%
Two phase short circuit	30	30	100%
Three phase short circuit	30	30	100%
Transformer operation	30	29	96.67%
Induction motor start	30	30	100%

operation, the classification and identification accuracy results of test samples are shown in Table 2 and Fig. 11, respectively.

It can be seen from Table 2 and Figs. 2 and 1 that the correct identification rate of single-phase grounding short-circuit fault, two-phase short-circuit, three-phase short-circuit and induction motor startup has reached 100%, while there is only one identification error when the transformer is put into operation, and the correct rate is about 97%.

In order to verify the superiority of the recognition accuracy of extracting the energy entropy of voltage sag signal IMF based on EMD and then inputting it into GWO-SVM classifier, a comparative study is set up under

Table 3
Recognition Accuracy of Six Different Classifiers

Classifier	Test Sample Size	Correct Identification Quantity	Correct Recognition Rate	Identification time/s
SVM	150	139	92.67%	13.616
PSO-SVM	150	136	90.67%	10.882
IPSO-SVM	150	143	95.33%	5.6736
GSA-SVM	150	143	95.33%	2.6125
ABC-SVM	150	145	96.67%	9.9596
GWO-SVM	150	149	99.33%	2.3679

the condition of ensuring that the training sample size and test sample size are the same. It is compared with SVM, particle swarm optimisation SVM (PSO-SVM), improved particle swarm optimisation SVM (ipso-SVM) The gravity search algorithm optimised SVM (GSA-SVM) and artificial bee colony algorithm optimised SVM (ABC-SVM) are compared, as shown in Table 3.

It can be seen from the data in Table 3 that the accuracy of GWO-SVM classifier in identifying a single voltage sag source is higher than that of the other five common traditional classifiers. GWO-SVM classifier has efficient recognition ability. The GWO is used to optimise the penalty factor Q of SVM and the parameters in the kernel function to construct GWO-SVM classifier. Compared with other traditional five classifiers, GWO-SVM classifier can effectively improve the recognition accuracy of different voltage sag sources, and the recognition time is less than the traditional five classifiers. Therefore, in terms of recognition accuracy and recognition speed, GWO-SVM classifier has more general applicability, can meet the needs of quickly identifying voltage sag sources, and has very important reference value and significance for solving practical process problems.

6. Conclusions

In this paper, the causes of voltage sag caused by short-circuit fault, transformer switching and induction motor starting in distribution network are analysed in detail. In order to quickly judge the type of voltage sag source that may occur, a voltage sag source identification method based on EMD energy entropy and GWO-SVM classifier is proposed. The method is verified by simulation data, and the following conclusions can be drawn:

In order to accurately identify the voltage sag source, the energy entropy is extracted as the feature vector of the voltage sag signal, and a good identification accuracy is obtained.

Using GWO to optimise SVM can effectively avoid falling into local optimisation in the optimisation process of traditional SVM, improve the recognition accuracy from 92.67% to 99.33%, and shorten the time from 13.616 s to 2.3679 s, which greatly improves the accuracy and rapidity of voltage sag source identification.

Compared with SVM, PSO-SVM, ipso-SVM, gsa-SVM, and abc-SVM, GWO-SVM classifier has the highest recognition accuracy, reaching 99.33%, faster speed and the least time. It can quickly and accurately identify five common voltage sag source types in only 2.3679 s.

The voltage sag source identification method based on GWO optimised SVM mentioned in this paper can quickly and accurately identify the types of voltage sag, which provides a new idea for solving practical engineering problems. Its theory is simple and has strong practicability. It is a very effective voltage sag source identification method, it helps to improve the economy and reliability of the whole power system.

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Biographies

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