Fault Feature Selection for Distribution Network

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Abstract. For the connection of DGs in distribution network, the fault power flow is different from that in normal operation. Further, the size of the fault current is limited by the electronic components and greatly reduces. Therefore, fault detection, the protections and their coordination become very complex. Fault detection technology helps to achieve fault isolation and recovery, and plays an important role in distribution network control and operation. This paper proposes a data-driven fault feature selection method for distribution network. This method collects various electrical quantities during normal and short-circuit faults of the distribution network as a feature library, and uses the support vector machine-recursive feature elimination method for feature selection to remove redundant features. The optimized fault features can be used to fault detection for distribution network with DGs.

Keywords: Feature Selection, Machine Learning, Fault Detection

1 Introduction
Due to the large number of micro-sources within the distribution network, diverse output characteristics and complex network structure, traditional protection is no longer applicable. [1-3] Therefore, it is extremely important to study a new fault detection method for distribution network. [4-8]

Although the above References used data mining algorithm for fault detection, none of them made feature selection to remove redundant features. Based on the above situation, this paper proposes a data-driven fault detection scheme for distribution network. When the plan to collect the normal and fault of distribution network as the Feature library, various electric parameters to use Support Vector Machine (SVM) of all the characteristics of the feature selection. [9, 10]

2 Distribution Network Model

2.1 Distribution Network Topology
This paper adopts a typical configuration in the distribution network as shown in Fig. 1.
The typical structure of distribution network includes multiple feeders on which distributed power supply and load are connected. The distribution network is connected to the external network through switches and common connections. In a typical distribution network, the power supply of the distribution network can be divided into four categories, namely photovoltaic power generation, wind power generation, fuel cell and micro gas turbine. Distribution network load can be divided into three categories, namely sensitive load, adjustable load and non-sensitive load.

2.2 Control Method of Inverters
In the distribution network, the inverter of distributed power supply is the key device for renewable energy generation to transmit electric energy to the grid or load, and the choice of control method will seriously affect the power quality of distributed power generation.

3 Feature Selection Algorithm based on SVM

3.1 SVM Algorithm
SVM is a supervised machine learning algorithm, which is often used in dichotomy problems. Compared with other learning methods, it can improve the generalization ability through the principle of structural risk minimization, and can effectively avoid overfitting. It can be formalized as a convex optimization problem, so that the solution obtained must be the global optimal solution and avoid falling into the local optimal solution. The basic idea of SVM is to learn the sample solution for a maximum separation hyperplane.

Suppose the training sample set \( T=\{(x_i,y_i)\} (i=1,2...,n) \), where \( n \) is the number of samples, \( (x_i, Y_i) \) is a sample instance, \( X_i \) is the feature of the sample, and \( Y_i \) is the label of the sample. In this paper, there are six categories of multi-classification problems, so \( y_i \in \{1,2,3,4,5,6\} \), in which 1,2,3,4,5,6 respectively represent normal, single-phase ground fault, two-phase ground fault, three-phase ground fault, two-phase ground fault, three-phase ground fault, three-phase ground fault and three-phase ground fault.

In the dichotomy problem, SVM aims to find an optimal separation hyperplane \( w^T+b=0 \) to maximize the classification interval. The classification interval value is \( 2/\|w\| \), where \( w \) is the weight vector of the feature and \( b \) is the bias. The optimization problem of SVM is shown in formula (1).
In general, there are some outliers in the sample, which lead to linear inseparability of the sample. After removing these outliers, the other samples can be linearly separable. To avoid this situation, an additional relaxation variable $\xi$ was added to the constraint (1), where the optimization problem is shown in formula (2).

$$
\begin{align*}
\min_{w,b,\xi} & \quad \frac{1}{2} \|w\|^2 + C \sum_i \xi_i \\
\text{s.t.} & \quad y_i \left( w \cdot x_i + b \right) - 1 \geq 0, \quad \xi_i > 0
\end{align*}
$$

(2)

Where $C > 0$ is the penalty parameter.

For sample $x_i$, the hyperplane is separated as shown in formula (3).

$$
f(x_i) = w^T x_i + b
$$

(3)

SVM classification decision function is shown in Formula (4).

$$
y_i = \text{sign}(f(x_i))
$$

(4)

For nonlinear problems, SVM can use kernel functions. The basic idea is to build a classification hyperplane in a high-dimensional space by mapping the original data to the high-dimensional space. The radial basis function is the most commonly used kernel function of SVM, as shown in formula (5).

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

(5)

Where $x_i$ is the expected value of the sample and $\sigma$ is the kernel parameter.

The above are dichotomous problems, and the OVO method is adopted in this paper. OVO principle aims to find pair combinations of all different categories in the training set, including $P = k(k-1)/2$ combinations, in which $k$ is the number of categories, $P$ prediction results can be obtained. The sample category with the most predicted results is regarded as the final prediction category of this sample.

3.2 SVM Algorithm

This article selects the 18 candidates characteristics, namely the three phase current $I_a, I_b, I_c$, three-phase voltage $U_a, U_b, U_c$, active power $P$, reactive power $Q$, frequency $f$, I0 zero sequence current, positive sequence current $I_1$, negative sequence current $I_2$, three phase current differential $dI_a/dt, dI_b/dt, dI_c/dt$, three-phase voltage differential $dU_a/dt, dU_b/dt, dU_c/dt$.

In this paper, the SVM algorithm is used to select the electrical characteristics of the distribution network, and the characteristics that can distinguish the normal operation and fault operation of the distribution network to the greatest extent are selected as the optimal characteristics. The steps of feature selection of SVM algorithm are designed as follows:

Step 1: All electrical features of the distribution network are taken as input and all features are taken as feature sets.

Step 2: SVM with the current data, calculates the weight $w$ of all features are taken as the sorting criterion, sorts the features of the current subset in descending order according to $w_2$, removes the features at the end of the sorting of the current subset, and puts the serial number of the removed...
features into the feature selection order table, so as to display the order in which each feature is removed.

Step 3: The feature subset and the remaining features form a new data set. Repeat step 2 until only one feature remains in the feature subset.

Step 4: Output the sequence table of feature selection and the classification accuracy of each feature subset.

The flow chart of SVM algorithm is shown in Fig. 2.

4 Examples Analysis

4.1 Data Collection

The simulation time of the distribution network model is 0s-1s, and the failure time is 0.6s-0.7s. The normal and fault conditions of distribution network under different operating conditions are as follows:

1) Change the active power of load L1 and set it as 0.2MW, 0.4MW, 0.6MW, 0.8MW and 1MW, respectively.
2) Change the Angle of phase A failure and set it as 0°, 45°, 90°, 180° and 270°, respectively.
3) Change the location of the fault and set it as F1, F2 and F3 respectively.
4) Change the excessive resistance, set to 0.01Ω and 0.1 Ω respectively.

A total of 900 sets of data were collected, each set of data had 18 features, and a total of 18,900 sample data were collected.

4.2 Feature Selection

![SVM algorithm flow](image-url)

Fig. 2 SVM algorithm flow
In this paper, SVM is used to select 18 features in the distribution network, and the classification accuracy is taken as the index to determine whether to select such features. The change of fault classification accuracy of distribution network with the number of features is shown in Fig. 3.

![Fig.3 Variation curve of microgrid fault classification accuracy rate with number of features](image)

**Fig.3** Variation curve of microgrid fault classification accuracy rate with number of features

All features in the distribution network are ranked by weight from large to small as follows:

\{ U_a, I_1, I_2, I_0, P, U_b, I_c, I_a, U_c, I_b, dI_a/dt, Q, dI_b/dt, dU_b/dt, dU_a/dt, dI_c/dt, f \}

It can be seen from Fig.3 that, when the number of features is 8, the fault classification accuracy of distribution network not only no longer changes significantly, but also drops a little. Therefore, redundant features should be removed to prevent these features from interfering with fault classification. 10 features are removed from the 18 features of the distribution network, and the remaining 8 features are the best feature collection, and the best feature collection is \{ U_a, I_1, I_0, I_2, P, U_b, I_c, I_a \}.

5 Conclusions

This method uses SVM algorithm to select electrical features in distribution network, remove irrelevant features and redundant features, select the most sensitive features, and obtain the optimal subset of features. For further the optimal features can be used to fault detection for distribution network.

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