Fault diagnosis of modular multilevel converter based on principal component analysis and support vector machine

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Abstract. Modular multilevel converter (MMC) is widely used in DC transmission, new energy grid-connected power generation, transmission, reactive power compensation, power flow control and other fields. When the sub-module fails, detecting and locating the fault quickly and accurately is the key to improving the operational reliability of the converter. Principal component analysis (PCA) obtains the feature space of reduced dimension by extracting the principal components of the fault sample set, which is conducive to the extraction of fault features. Support vector machine (SVM) has good classification performance when applied to fault diagnosis. Combining the advantages of both, this paper takes modular multi-level converter as the research object, extracts the fault characteristics of MMC, and uses PCA algorithm to reduce dimensionality. Then, the SVM classifier is constructed, the processed fault samples are used for training, and the trained SVM classifier is used to perform fault diagnosis. Finally, a three-phase eleven-level MMC simulation model is built to simulate the method used. The results show that this method can effectively improve the diagnosis speed and accuracy of MMC fault diagnosis, and provides a reference for the application of the PCA-SVM method in the actual engineering of MMC fault diagnosis.

1. Introduction

With the continuous increase in the scale of new energy installations and the gradual development of intelligent power grids, modular multilevel converters are increasingly used in fields such as flexible DC transmission and new energy grid connection. Each bridge arm of the MMC is composed of multiple sub-modules (SM) with the same parameters in series and divided by voltage, failure of any sub-module will cause the bridge arm to work abnormally and affect the normal operation of MMC. Therefore, when a sub-module fails, the fault can be quickly and accurately determined and the faulty sub-module can be replaced through a redundant control strategy, which can greatly improve the reliability of MMC operation[1].

Among the components of MMC, the power device of the sub-module is the component with the highest failure rate. The short-circuit fault of the power device is generally detected by the hardware protection circuit, and the scheme is relatively mature, while the open-circuit fault of the power device is not easy to find[2], but it will cause serious damage to the system if it is allowed to develop. The open-circuit fault diagnosis methods for MMC sub-modules at home and abroad mainly include hardware-based methods[3], model-based methods[4], and machine learning-based methods[5]. Literature [5] proposes a pattern recognition method based on K-means clustering, which detects and locates faulty sub-modules through the two-dimensional trajectory pattern of sub-modules, but this method is computationally intensive and complex. Literature [6] proposes a feature extraction and
dimensionality reduction method based on the combination of WPD and PCA, then the optimized BP neural network is used to achieve fault location. Literature [7] summarizes the fault operation characteristics when different faults occur through simulation analysis, and provides a reference for accurately locating MMC faults.

This paper selects the fault diagnosis and identification method of power electronic rectifier device based on the combination of PCA-based fault feature extraction and support vector machine, and applies this method to the open-circuit fault diagnosis of the MMC sub-module. Firstly, this paper studies the mechanism of MMC under normal operation and fault conditions, and selects the signal that best reflects the open circuit fault of the sub-module as the fault characteristic parameter; Secondly, the PCA algorithm is used to reduce the dimensionality of the fault feature, the SVM classifier is constructed, the processed fault samples are used for training, and then the trained SVM classifier is used for fault diagnosis; Finally, an MMC simulation model is built to verify the fault diagnosis method used.

2. Open-circuit fault analysis of MMC sub-module

At present, the most commonly used MMC topology in engineering is shown in Figure 1, and its submodule structure is a typical half-bridge structure[8].

![ MMC topology diagram ]

Figure 1. The topology of MMC

In Figure 1: $U_d$ and $I_d$ are the DC side voltage and current; $i_{pj}$ and $i_{qj}$ (j = a, b, c) are the currents of the upper and lower bridge arms; $T_1$ and $T_2$ are sub-module switch tubes; $i$ is the current of the sub-module; $U_c$ is the capacitor voltage of the sub-module.

There are four modes in the internal current path of the sub-module when the MMC is running normally, as shown in Table 1.

| Mode | $T_1$ | $T_2$ | $i$ | Flow through the device | Capacitance state | status |
|------|-------|-------|-----|-------------------------|-------------------|--------|
| 1    | 1     | 0     | >0  | $D_1 - C$              | Recharge          | Put in |
| 2    | 1     | 0     | <0  | $C - T_1$              | Discharge         | Put in |
| 3    | 0     | 1     | >0  | $T_2$                  | bypass            | resection |
| 4    | 0     | 1     | <0  | $D_2$                  | bypass            | resection |
Analysis of Table 1 shows that if $T_1$ fails, it will affect the circuit in mode 2; if $T_2$ fails, it will affect the circuit in mode 2;

Figure 2 shows the internal operation of the sub-module with $T_1$ open circuit in mode 2 and $T_2$ open circuit in mode 3. According to Figure 2(a), $T_1$ open circuit in mode 2 causes the capacitor to be unable to discharge through $T_1$; Figure 2(b), $T_2$ open circuit in mode 3 causes the capacitor to be bypassed by $T_2$ and forced to charge.

Figure 2. The internal operation of the sub-module during an open-circuit fault

Based on the above analysis of the internal operation characteristics of the sub-module after the open circuit fault of the power transistor, when an open-circuit fault occurs in the sub-module, the flow path of the bridge arm current inside the sub-module will change in a specific mode, resulting in changes in the bridge arm current, output voltage and three-phase AC current.

3. Fault detection method based on PCA-SVM

This paper presents an MMC fault diagnosis method based on the PCA-SVM algorithm model, and then introduces the theoretical principles of the method used.

3.1. Fault feature extraction based on PCA

According to the principle of PCA, the feature extraction algorithm of fault signal based on PCA is as follows.

- Step 1. The sampling points of $t$ single fault signals constitute a one-dimensional column vector $x = [s_1, s_2, \cdots, s_t]^T$. The total number of fault signal samples used for training is $N$, each fault signal sample is $t$ dimensional, then these fault signals are extracted by row into the corresponding column vector as $x_1, x_2, \cdots, x_N$.

- Step 2. Calculate the average of the entire sample

$$m = \frac{1}{N} \sum_{i=1}^{N} x_i \quad (1)$$

- Step 3. Calculate the covariance matrix:
\[ C_i = \frac{1}{N} \sum_{i=1}^{N} (x_i - m)^T(x_i - m) = \frac{1}{N^{1/2}} \frac{1}{N^{1/2}} \sum_{i=1}^{N} (x_i - m)^T = XX^T \]  
\[ X = [(x_1 - m), (x_2 - m), \ldots, (x_N - m)] / (N^{1/2}) \]  

Step 4. Solve the eigenvalues and eigenvectors of the covariance matrix, that is, solve the eigenvalues of the construction matrix \( Cx = XX^T \) and the corresponding orthogonal normalized eigenvectors \( \xi_i \).

Step 5. Solve the matrix \( A \). When the dimension of the original fault signal is much larger than the fault training sample, that is
\[ t >> N, \quad \zeta_i = X\xi_i / \lambda_i^{1/2}, (i = 1, 2, \ldots, N) \]  
There is \( A = (\xi_1, \xi_2, \ldots, \xi_N) \).

Step 6. Project the vector in the training sample of each fault signal to the subspace formed by the feature vector \( A \), that is
\[ y_i = A^T x_i, (i = 1, 2, \ldots, N) \]

Through the above steps, the N-dimensional feature vector of the fault signal can be effectively extracted.

3.2. Improved SVM multi-classification algorithm

Support Vector Machine is a generalized linear classifier for binary classification of data. The algorithm is derived from the two-class classification problem, which is proposed in the case of linear separability. For general nonlinear problems, nonlinear transformation is achieved by defining an appropriate kernel function, the input space is transformed into a high-dimensional space, and then the optimal linear classification surface is found in this new space[9].

SVM was originally proposed for two classification problems, and the converter fault diagnosis not only determines whether the rectifier is faulty, but also determines the location of the fault. It is a multi-value classification problem, and multiple second-class SVM classifiers need to be combined to construct the SVM multi-classifier.

Taking into account the structural characteristics of the converter circuit itself, the original "one-to-many SVM" algorithm is improved here. Specific improvement ideas include:

- When constructing the \( i \)-th classifier of the N fault type classifiers, the fault training samples belonging to the \( i \)-th SVM are regarded as one category, and the category label is 1, the other remaining training samples are regarded as one category, and the category label is -1.
- In order to improve the accuracy of diagnosis, the process of classifying fault test samples is improved. The decision function used is still
\[ f_i(x) = \text{sgn}(\omega^i \phi(x) + b^i) \]  
The improved classification process is shown in Figure 3.
begin

Current sampled value in(k), out(k)

Calculate error(k), which is e(k)

Calculate the rate of change of error(k), which is ec(k)

Blur e(k) and ec(k)

Look up tables based on fuzzy rules and decisions

Get the value of Kp, Ki and Kd

Calculate the current value of Kp, Ki and Kd

Parameter output, return to the next moment in(k+1), out(k+1), Continue to solve

Figure 3. Fault classification flowchart

3.3. Fault diagnosis based on PCA-SVM

According to the basic principle of SVM and the fault feature extraction algorithm of PCA, a PCA-SVM-based MMC fault diagnosis and identification method is proposed. The application of this method in the field of converters fully reflects its advantages. The specific implementation steps based on the PCA-SVM fault diagnosis and identification method are as follows.

- Step 1. Extract the original feature sample set of the fault signal to form the fault diagnosis feature vector in the high-dimensional feature space.
- Step 2. According to the PCA fault feature extraction algorithm, the dimensionality of the data is reduced. After transforming the high-dimensional feature space, a new set of principal components is obtained to form a low-dimensional feature space. By calculating the fault feature vector in the low-dimensional feature space, the N-dimensional feature vector of each fault signal is obtained to form a feature vector for fault identification.
- Step 3. The fault diagnosis SVM model established is shown in Figure 4. According to the feature vector obtained in step 2, the training sample set is established. The appropriate kernel function and related parameters of the SVM are determined according to the actual situation, and the training sample set is sent to the SVM classification model for training.

Figure 4. Fault diagnosis SVM model
Step 4. The fault training sample or test sample extracts the N-dimensional feature vector by PCA, which is used as the input of the trained SVM multi-classifier, and the output of the SVM is the corresponding fault type, so as to realize fault diagnosis and fault location.

4. Simulation
In order to verify the correctness of the PCA-SVM-based fault diagnosis method, this paper builds a three-phase eleven-level MMC simulation model based on the MATLAB/SIMULINK platform. For an eleven-level MMC inverter system, each phase has two upper and lower bridge arms, and each bridge arm is composed of a current-limiting reactor and ten sub-modules in series. The simulation model diagram is shown in Figure 5.

![Eleven-level MMC simulation model](image)

Figure 5. Eleven-level MMC simulation model

Figure 6 shows the A-phase output voltage and A-phase bridge arm current waveform during normal operation. The A-phase output voltage amplitude is about 4500V, which conforms to the set DC voltage parameters, and the waveform shape is an eleven-level ladder, approaching a sine wave. The current waveform of the A-phase bridge arm is completely symmetrical and without distortion, which verifies the correctness of the model.
This article assumes that the first sub-module T1 of MMC’s A-phase upper bridge arm has an open circuit fault at 2s. The A-phase output voltage and bridge arm current waveforms in the time domain are transformed into the frequency domain through Fourier transform, then the power spectrum values of 15 key frequency points are collected to form a feature vector.

150 data samples are selected for each failure mode in the low-dimensional feature space, each sample contains 15 feature components, and the feature training set (50 samples for each failure mode) and test set (100 samples for each failure mode) are selected to construct the SVM classifier for training and fault diagnosis. In order to ensure high classification accuracy, this paper chooses RBF as the kernel function, and the kernel width is 6.

Taking the fault set in this article as an example, the final diagnosis accuracy distribution of training samples and test samples is shown in the Table 2.

| Fault type                  | Number of training samples | Training sample accuracy(%) | Number of test samples | Test sample accuracy(%) |
|-----------------------------|----------------------------|-----------------------------|------------------------|-------------------------|
| Open circuit fault of $T_1$ | 50                         | 100                         | 100                    | 94.13                   |

The results show that when the PCA-SVM algorithm is used in the field of MMC fault diagnosis, for the fault training samples, the recognition rate is basically 100%, and for the test samples, the recognition rate can reach close to 95%, which effectively improve the diagnosis accuracy of MMC fault diagnosis.

5. Conclusion
Modular multilevel converters have a large number of sub-modules, which increases the probability of failure of sub-modules. Therefore, rapid diagnosis and accurate location of sub-module faults are important guarantees for continuous and uninterrupted operation of the converter. This paper analyzes the change characteristics of the bridge arm current and the sub-module capacitor voltage in each working mode when the MMC sub-module has an open-circuit fault, and introduces a PCA-SVM-based fault detection method, which combines the advantages of the PCA and SVM algorithms respectively. First, the fault signal is compressed by principal components and the fault feature vector is extracted, then the extracted fault feature vector is sent to the SVM classifier for training and fault diagnosis. This article uses the above-mentioned method to simulate the fault diagnosis of MMC. The results verify the correctness and effectiveness of the method applied to MMC fault diagnosis. In addition, this method combines the advantages of PCA and SVM algorithms, which can also be extended to other forms of power electronic equipment fault diagnosis, and for the simultaneous failure of multiple sub-modules of the same bridge arm in MMC, further research can be carried out.
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