Fault Detection Method of Electronic Circuit Converter Based on Dynamic Sequence Response

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Abstract. Traditional electronic circuit converter fault detection methods take local eigenvalues as eigenvectors to analyze. In the actual work process, different factors will lead to the difference of electronic circuit converter features, which leads to the low accuracy of feature classification. Therefore, this paper designs an electronic circuit converter fault detection method based on dynamic sequence response. Firstly, the data collector is designed to complete the collection of electronic circuit converter signal, the analysis model based on dynamic sequence response analysis method is established, the short-circuit fault signal feature extraction based on wavelet transform, the fault detection classifier is optimized, the fault location algorithm is optimized, and the design of electronic circuit converter fault detection method based on dynamic sequence response is completed. The experimental results show that the accuracy of the traditional method is only 25.3%, and the accuracy of the designed method can reach 88.7%, which verifies the effectiveness of the design method.

Keywords: Dynamic sequence response · Electronic circuit · Converter fault detection

1 Introduction

With the rapid development of power electronic technology and the continuous expansion of power electronic device market, as the core part of the whole power conversion, electronic circuit converter industry, energy, transportation, national defense and other fields play an increasingly important role. According to statistics, about 75% of electric energy in developed countries is used after power electronic converter technology, which is expected to reach more than 95% soon. However, the following converter circuit fault problem is also increasingly prominent [1–3]. Due to the wide use and importance of power electronic converter technology in various application fields, the reliability of these devices with converter circuits is required to be higher and higher. Once the fault occurs, especially the open circuit fault of the device, if the fault of the converter circuit can not be correctly diagnosed and repaired in time, it will cause waveform distortion and system instability, or direct shutdown, or even damage the equipment and personnel, and bring huge economic losses and accidents. Especially in aviation, national defense and other application fields with high

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requirements for equipment reliability, it is more necessary to ensure the timely and accurate diagnosis of converter circuit device in case of fault [4, 5]. Therefore, it is of great significance to propose intelligent, fast and accurate fault diagnosis method for power electronic converter circuit.

In reference [6], an improved floating board modulator and a fault detection circuit for positive and negative bias voltage are proposed. By using the parasitic capacitance characteristics of MOSFET, the modulation pulse width is controlled by a fixed pulse width, and the output negative bias voltage is increased by adding a negative bias MOSFET. In reference [7], a fault protection scheme for overhead flexible direct power grid with reactor voltage difference is proposed. In this scheme, the difference of positive and negative reactor voltage amplitude is used for fault pole selection, and the sum of positive and negative reactor voltage is used for fault detection.

In the traditional detection methods of electronic circuit converter fault, the current time and current value and other local eigenvalues are used as eigenvectors to analyze. However, in the actual working process, the operating conditions, manufacturing process, circuit breaker model and operating time will lead to certain differences in the current eigenvalues of electronic circuits. The traditional methods have certain limitations. The accuracy of feature classification is low. Therefore, this paper designs an electronic circuit converter fault detection method based on dynamic sequence response. The data collector is designed to complete the collection of electronic circuit converter signal, the analysis model based on dynamic sequence response analysis method is established, the feature extraction of short circuit fault signal based on wavelet transform, the fault detection classifier is optimized, the fault location algorithm is optimized, and the electronic circuit converter fault detection based on dynamic sequence response is completed.

2 Fault Detection Method of Electronic Circuit Converter Based on Dynamic Sequence Response

2.1 Acquisition of Electronic Circuit Converter Signal

For the current signal acquisition of electronic circuit, the most commonly used method is to use the open-ended Hall current sensor. In the measurement process, the incoming line on one side of the electromagnet in the electronic circuit is connected with the sensor, and the acquisition signal is transmitted from the sensor to the data acquisition card through the NBC interface [8–10]. In the process of current signal measurement, the collected electronic circuit converter signal will be affected by the electromagnetic interference in the process of equipment operation, external environment and transmission, including some random and irregular noise, which makes the current signal distorted. These noises will disturb the characteristic information of the original current waveform.

Data collector is an important source of monitoring electronic circuit operation data, which mainly completes the voltage and current phasor acquisition. FPGA is mainly used to control the ad chip. After receiving the GPS clock signal, FPGA triggers the ad chip through a series of processing such as frequency division [11–13]. In order to ensure the requirements of data acquisition and transmission, a SMV (sampling measurement value) interface is designed in the data collector. The interface can efficiently and quickly complete the acquisition and transmission of waveform data, and reduce the delay. Using SMV for fast transmission of sampling points can solve the throughput capacity of big data. The data transmission of SMV message occurs at the data link layer, and its message format is shown in the following table (Table 1):

Table 1. SMV message format

MAC frame content	Explain	Number of bytes
Preamble (preamble)	The receiver realizes synchronization and extracts clock information	8 bytes
Frame start delimiter (SFD)	Represents the beginning of a frame. 1 and 0 in the field are used interactively to mark the beginning of valid data	1 byte
Header MAC	Mac destination address	16 bytes
Priority tagged	0 × 210XXA03000–0 × 210XXA0303ZZ	2 bytes
Byte padding	It is used to distinguish the eight priorities	0–32 bytes
CRC check	TPIO = 0 × 2100	4 bytes
Ethertype	APPID = 0 × 2000–0 × 210XX	2 bytes

Eight analog channels are designed in the collector, each channel is compatible with current and voltage, and the input current range is 0–5 A, the input voltage range is 0–350 V.

The data collector of electronic circuit needs to have the function of phasor measurement in the process of operation. It needs to have a higher sampling range, and make the data signal of the acquisition band present the completed waveform. Therefore, the data collector needs to have the characteristics of high range and high precision, and it needs to add current transformer and voltage transformer [14–16]. TS24D43-100 A/30 mA is used as the current transformer. The measurement range of this type of transformer is wide and the accuracy is high. The voltage transformer is ZWQ281A. The conversion accuracy of this type of transformer is very high, which is suitable for the monitoring of micro equipment. The detailed parameters of the two transformers are shown in the table below (Table 2):

Table 2. Transformer parameters

Transformer type	Project	Detailed parameters
Current transformer	Rated input/output current (mA)	10 A/0.5
	Rated point difference (%)	$\leq \pm 0.1$
	Load (Ω)	≤ 120
	Accuracy class	0.1
	Linear range	5%In–2000%In
Voltage transformer	Rated input current (mA)	1 A
	Rated output current (mA)	1 A
	Transformation ratio	1000: 1000
	Phase difference	≤ 20’ (input is 1a, sampling resistance is 100 Ω)
	Linear range	0–1000 V, (sampling resistance is 100 Ω)
	Permissible error	$-5\% \leq f \leq 0$ (sampling resistance is 100 Ω)
	Working temperature	−40 °C ± 85 °C

After the data collected is processed by the two transformers, the sampling value sequence is obtained, which has 8 channels, each channel has 8 bytes, which represents the effective data quality of the sampling value, which determines the effectiveness of the channel [17, 18].

In order to detect the current change fault of electronic circuit, it is necessary to extract the noise free waveform of the electronic circuit, so as to improve the accuracy of fault detection. Therefore, the collected electronic circuit is transformed into a stream. In this paper, the five point three smoothing method is used to filter the noise. Assuming the format of the experimental data is $Y_{-n}, Y_{-n+1}, \ldots, Y_0, Y_1, \ldots, Y_n$, some isometric nodes $X_{-n}, X_{-n+1}, \ldots, X_0, X_1, \ldots, X_n$ are set, and the distance between the equidistant nodes is h. The nesting between the experimental data and the equidistant nodes can be completed. After the relevant exchange calculation, the data can be nested with the equidistant nodes. The experimental data can be fitted and calculated

$$Y(t) = a_0 + a_1 t + a_2 t^2 + \ldots + a_m t^m \tag{1}$$

In the above formula, t can be expressed as $t = \frac{x - x_0}{h}$, which is the functional form of exchange calculation. For the undetermined coefficients in the above formula, the least square method is needed to solve them:

$$\sum_{i=-n}^{n} R_i^2 = \sum_{i=-n}^{n} \left[\sum_{j=0}^{m} a_j t_i^j - Y_i \right]^2 = \phi(a_0, a_1, \ldots a_m) \tag{2}$$

For the above formula, the objective of the least square method is to minimize $\phi(a_0, a_1, \ldots a_m)$. Therefore, it is necessary to find the partial derivative of the above formula for $a_k(k = 0, 1, \ldots, m)$, so that the partial derivative is 0, and the derivative equation of the following formula is obtained:

$$\sum_{i=-n}^{n} Y_j t_i^k = \sum_{j=0}^{m} a_j \sum_{i=-n}^{n} t_i^{k+1} \tag{3}$$

In this paper, the five point cubic smoothing method is used to carry out simple noise filtering, that is, the values of n, m in the above formula are 2 and 3 respectively, so that five nodes can be obtained, and t can be assigned to obtain the final five point cubic smoothing equation system

$$\begin{cases} \overline{Y}_{-2} = \frac{1}{70}(69Y_{-2} + 4Y_{-1} - 6Y_0 + 4Y_1 - Y_2) \\ \overline{Y}_{-1} = \frac{1}{30}(2Y_{-2} + 27Y_{-1} + 12Y_0 - 8Y_1 + 2Y_2) \\ \overline{Y}_0 = \frac{1}{35}(-3Y_{-2} + 12Y_{-1} + 18Y_0 + 12Y_1 - 3Y_2) \\ \overline{Y}_1 = \frac{1}{35}(2Y_{-2} - 8Y_{-1} + 12Y_0 + 27Y_1 + 2Y_2) \\ \overline{Y}_2 = \frac{1}{70}(-Y_{-2} + 4Y_{-1} - 6Y_0 + 4Y_1 + 69Y_2) \end{cases} \tag{4}$$

The de-noising method selected in this paper requires at least five nodes. In order to ensure the symmetry of the original electronic circuit converter signal in the de-noising process, different equations need to be selected for processing in different parts of the electronic circuit converter signal [19–21].

2.2 The Analysis Model Based on Dynamic Sequence Response Analysis Method is Established

Dynamic sequence response analysis is to arrange a group of random sequences in order of time sequence, and use statistical method to deal with the dynamic sequence response value. In statistics, the less variables are analyzed, the simpler the process is, the higher the accuracy of the results is. Firstly, the historical characteristic data of the electronic circuit to be tested is obtained, and it is taken as a sample set x, and the samples are respectively expressed as $x_1, x_2, \ldots .x_n$. Then the maximum value, minimum value, average value and standard deviation of the sample set can be calculated, and the curve fitting can be performed to fit the distribution according to the probability distribution of the variable flow characteristic data. The distribution curve is tested by the method of distribution fitting goodness test. The chi square test is used. The formula of chi square value is as follows:

$$\chi^2 = \sum_{i=1}^{r} \frac{(n_i - m_i)^2}{m_i} = \sum_{i=1}^{r} \frac{(n_i - Np_i)^2}{Np_i} \tag{5}$$

In the above formula, n_i is the measured frequency of group i, m_i is the theoretical frequency, p_i is the probability that the observation results fall into group i, and N is the total number of samples. In the dynamic sequence response analysis algorithm, the correlation quantization calculation needs to pay attention to the current conversion data of the adjacent points of the observation point:

$$x_{t,w} = [x_t, x_{t+1}, \ldots, x_{t+w-1}]^T \tag{6}$$

In the above formula, t represents the initial time, w represents the sampling interval length, that is, the size of the window, and $x_{t,w}$ represents the window at time t. The function of time window is to obtain the local covariance matrix of each dynamic series response. In the selection process of time window, the weighted exponential sliding time window is selected as the basis of dynamic series response analysis. The interval of the time window is $1 \leq \tau \leq t$, and each window is multiplied by a factor $\beta^{t-\tau}$ to measure the value close to t, so the higher the weight is, the closer it is to the time window at t. When a dynamic sequence response T is known, the estimation formula of local autocovariance matrix at t time based on weighted exponential sliding time window is as follows:

$$\hat{\Gamma}_t = \hat{\Gamma}_{t-1} - T_{t-w,w} \otimes T_{t-w,w} + T_{t-w} \otimes T_{t-w} \tag{7}$$

In the above formula, $\hat{\Gamma}_t$ represents the estimation result of the local autocorrelation matrix. It can be seen from the above formula that the estimation formula has nothing to do with the w values in the earlier stage, which can improve the calculation efficiency. Because the matrix of similarity value after decomposition has many components, it needs to be filtered before it can be calculated and used [22, 23].

2.3 Feature Extraction of Short Circuit Fault Signal Based on Wavelet Transform

On the basis of the above analysis model based on dynamic sequence response analysis method, in order to realize the current transformation fault detection of electronic circuit, this paper uses wavelet transform to extract the short circuit fault signal of sub circuit to realize the fault detection. It is necessary to analyze the fault signal accurately to locate the fault quickly for quick maintenance. By establishing the identification model and comparing the amplitude and frequency components of the fault signal in the electronic circuit information database, the existing fault symptoms can be judged and analyzed quickly and accurately. Therefore, the complex wavelet transform is helpful to improve the fault diagnosis rate.

In the feature extraction of electronic circuit converter fault, the wavelet is the moving local signal in the fault:

$$D = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{8}$$

Where $\varepsilon^i(e)$ is the wavelet basis and s is the integrable function.

The wavelet function can accurately determine the fluctuation in the process of fault signal alternation, make it controlled in a reasonable range, and make it 0 in the average fluctuation range:

$$\int_{-\infty}^{\infty} \left|\varepsilon^i(e)\right|^2 dt = 0 \tag{9}$$

In the process of electronic circuit fault feature extraction, wavelet transform selection is also very important. The physical quantities and values of different nodes are also different. The input values of fault data are standardized in the range of [0, 0.1] and [0.9, 1.0], and the curve changes very flat in this range. The function formula of curve normalization is as follows:

$$T_i = Z_i - \frac{Z_{\min}}{Z_{\max}} - Z_{\min}\beta + \xi \tag{10}$$

Where, Z_i and T_i are the variables of normalization coefficient after wavelet transform, $Z_{\min}$ is the minimum ordinate of the curve after wavelet transform, $Z_{\max}$ is the maximum ordinate of the curve after wavelet transform, β is a constant in the process of curve transform, and the value of the constant will change according to the change of fault data input value, ranging from 1 to 1.5, take $\xi = \frac{1-\beta}{2}$. In the process of electromechanical fault detection, the nature and location of the fault are determined, including multi band energy, the time and amplitude of the maximum four points in these bands. These features are used to describe the input signal and serve as input signals. According to the travel time of wavelet in detection, the fault location is detected to realize the feature extraction of electronic circuit converter fault.

2.4 Fault Detection

Due to the wide distribution range of distribution network and numerous distribution equipment, the power consumption of distribution network devices is very different. Some old distribution lines and buildings are close to each other, and they are crossed or parallel with optical cables and various pipelines. When there is a fault, it will increase the complexity of troubleshooting. So we need to use fault location algorithm to detect fault information faster. At present, the original matrix algorithm can not determine the fault point at the end of the feeder, so the location algorithm is optimized.

The distribution network matrix of order $M \times M$ and the problem cause matrix of order $M \times M$ are constructed:

$$D = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{11}$$

Assuming that the number of distribution network nodes is M, when there is a feeder line between node i and node j, then the parameters in j column of each row i and i column of each row j in the matrix are represented by parameter 1. When there is information exceeding the maximum load current in FTU, a new fault information matrix G will appear

$$G = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{12}$$

When the fault current passes through the node j in the matrix G, that is, set the element G_{jj} to 1 and the others to 0. Multiply the matrix D and the matrix G to obtain the optimized fault location matrix P. When there is only one element in the device, in the event of a fault, after the fault current passes through the node i, the FTU of the node will transmit the information to the master station. After the master station receives the signal, the parameter of the matrix D is $D_{ii} = 1$, and the other elements in the matrix are set to 0. The signals received by the master station converge into an information collection matrix. When the parameter in the matrix is 1, it means that the i node has fault current and the direction is the same as the predicted direction; when the parameter in the matrix is 0, it means the i node. There is no fault current at each node; when the parameter in the matrix is -1, it means that there is an over fault current at the i node, but the direction is opposite to the predicted direction, so that the fault location can be completed.

3 Experiment

3.1 Experimental Data

In order to verify the effectiveness of the coil current fault automatic diagnosis method based on artificial intelligence algorithm designed in this paper, the mechanical fault simulation of high voltage circuit breaker is carried out in the experiment. Five states are selected: buffer spring fatigue, low voltage of control circuit, closing spring fatigue, transmission looseness and normal state, These five states are simulated in the machine for testing. Due to the space, this paper lists the coil current characteristic parameters under three mechanical states, as shown in the table below (Table 3):

Table 3. Coil current characteristics under three mechanical conditions

Characteristic quantity	Fatigue of buffer spring	Low voltage of control circuit	Closing spring fatigue
T_1/s	0.022	0.056	0.034
T_2/s	0.036	0.059	0.043
T_3/s	0.045	0.078	0.057
T_4/s	0.091	0.094	0.073
I_1/s	0.95	1.31	1.03
I_2/s	0.54	0.73	0.85
I_3/s	0.91	1.15	1.38
μ	0.154	0.256	0.354
σ	0.318	0.345	0.412
K	3.455	2.564	3.240
W/J	11.561	14.451	12.338

According to the characteristics of coil current in three different mechanical states in the above table, μ represents mean value, σ represents standard deviation, K represents kurtosis, and W represents energy parameter. Under the above experimental conditions, the simulation platform selected in this paper is the Simulink board contained in MATLAB7.0, and the power components in the power system Simulation toolbox are used to build the internal circuit module of the electromechanical system of the expressway.

In the above experimental environment, the fault setting of the simulation circuit diagram is carried out. Taking the fault location, fault type and the change of grounding resistance as the simulation conditions, the denoising effect of the improved single ended A-type traveling wave location method and the improved semi soft threshold denoising method is comprehensively simulated. The operation status of the circuit breaker is evaluated by using the above current characteristic parameters. The automatic diagnosis method of coil current can be transformed into the problem of data classification. Using artificial intelligence algorithm to identify and classify the current characteristics under the same state, the coil current fault is identified.

According to the cause and mechanism of coil current fault, this paper designs an experimental device to simulate coil current, as shown in the figure below (Fig. 1):

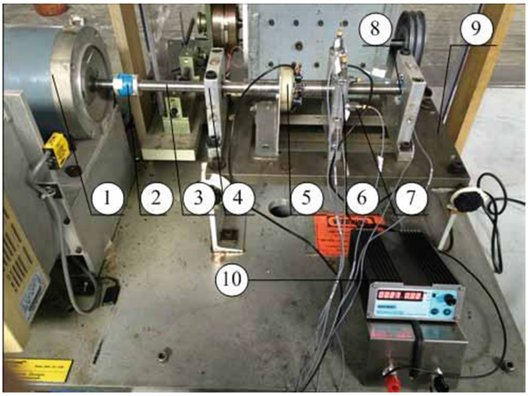

Fig. 1. Experimental platform of electronic circuit converter damage

In the figure above, ① represents the motor, ② represents the insulated coupling, ③ represents the coil spindle, ④ represents the coil support seat, ⑤ represents the coil current loading device, ⑥ represents the support seat of the test coil, ⑦ represents the vibration acceleration sensor, ⑧ represents the insulated coil, and ⑨ represents the base. ⑩ Represents the coil current simulator. In the process of signal acquisition, this paper uses the data acquisition system of pilse, which is mainly composed of data acquisition card, vibration acceleration sensor and acquisition system.

Under the above experimental conditions, we use the method designed in this paper and the traditional electronic circuit converter fault diagnosis method to carry out the experiment, and collect the current signal data of five different working states simulated in the experiment, 30 groups of data are collected under each working state, 24 groups of 30 groups of data are selected as the training set, and the remaining 6 groups are selected as the test set. Under the experimental design of the above formula, the experimental results of the two methods are statistically analyzed.

3.2 Experimental Results and Analysis

Under the above experimental conditions, the current feature classification results of the traditional electronic circuit converter fault diagnosis method and the diagnosis method designed in this paper are obtained respectively (Fig. 2):

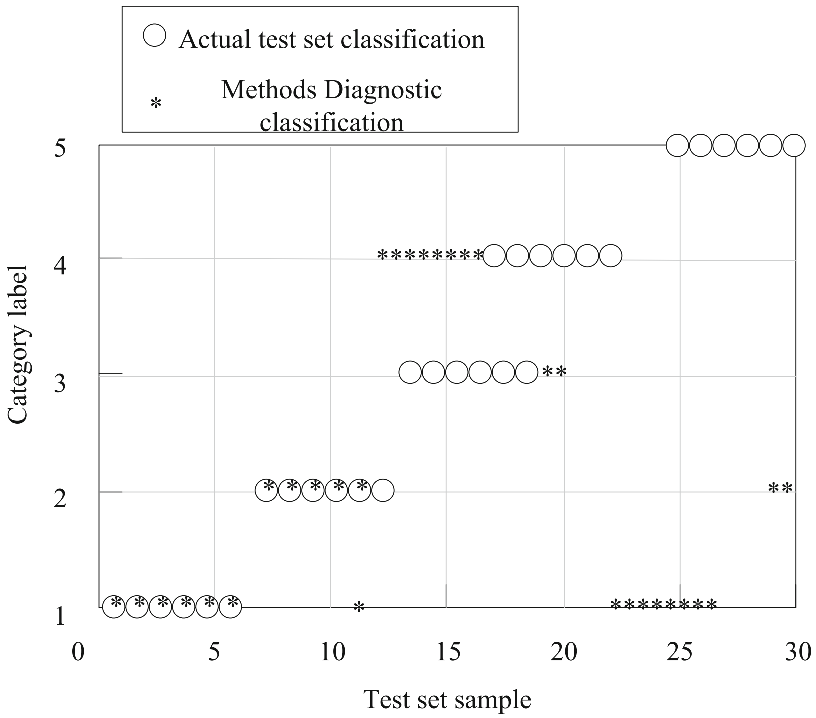

Fig. 2. Feature classification results of traditional methods

The test results of the electronic circuit converter fault detection method based on dynamic sequence response designed in this paper are as follows (Fig. 3):

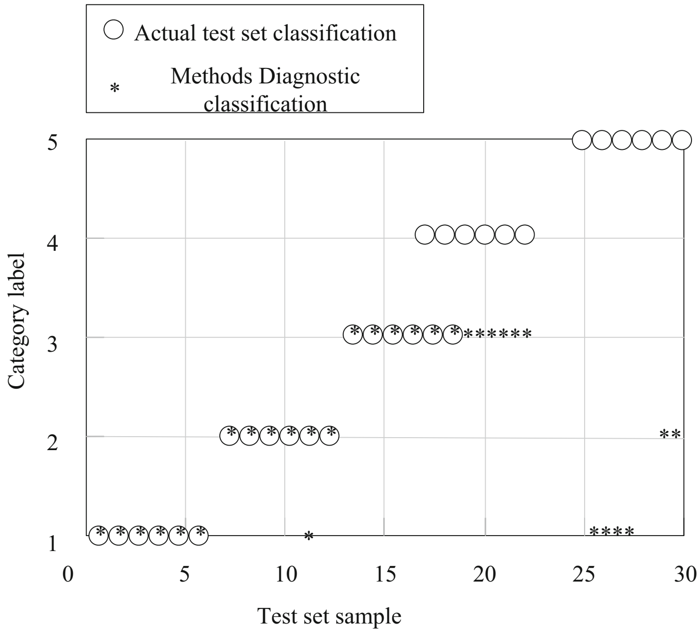

Fig. 3. Feature classification results of the method in this paper

It can be seen from the above two figures that the accuracy of fault identification and classification in the traditional method is only 25.3%, while the accuracy of fault identification and classification in this method can reach 88.7%, so from the accuracy of classification From the above, using the method in this paper can more fully diagnose the overall characteristics of the electronic circuit in the working process, and it is more reliable to classify and evaluate the types of current faults.

4 Concluding Remarks

In order to improve and enhance the efficient intelligent diagnosis method of power electronic converter circuit open circuit fault, aiming at the shortcomings of existing fault diagnosis methods in nonlinear and multi class classification problems, this paper deeply studies the open circuit fault diagnosis method of power electronic converter circuit, and proposes a detection method of electronic circuit converter fault based on dynamic sequence response. Firstly, the data collector is designed to complete the collection of electronic circuit converter signal, the analysis model based on dynamic sequence response analysis method is established, the short-circuit fault signal feature extraction based on wavelet transform, the fault detection classifier is optimized, the fault location algorithm is optimized, and the design of electronic circuit converter fault detection method based on dynamic sequence response is completed. The experimental results show that the accuracy of the traditional method is only 25.3%, and the accuracy of the designed method can reach 88.7%, which verifies the effectiveness of the design method.

At present, power electronic converter circuit fault diagnosis technology is still in the theoretical research stage, there are many aspects need to be further improved. In this paper, some work has been done on the fault simulation and diagnosis method of power electronic converter circuit, but there are still some work that is not deep enough and needs further research and exploration.

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