Abstract — This paper presents a method of fault features extraction based on the stacked auto-encoder (SAE), and this method can be used to rotating rectifier diodes open-circuit fault detection of brushless ac synchronous generator. First, exciter generator field current is collected, and then processed by Fast Fourier Transform (FFT) to obtain the frequency components. Secondly, these components are deeply learned and evaluated by the stacked auto-encoder to extract features automatically. Finally, fault detection can be carried out with Euclidean distance calculation. The algorithm is validated based on a brushless ac synchronous generator test rig, and the experimental results show perfect fault detection performance under different load conditions.

Keywords—Brushless AC synchronous generator; rotating rectifier; fault detection; stacked auto-encoder

I. INTRODUCTION

The brushless ac synchronous generators (BASGs) are the most popular and widely used power sources in aircraft and marine vessels for on-board power generation. It is also used as the shaft generator in the energy efficient hybrid electric ships for the propulsion systems [1]-[2]. Safety critical applications (e.g., more electric ships and aircraft), demand reliable BASGs to complete the mission reliably and safely [3].

Rotating rectifier is an important part in BASG, and this part eliminates the brushes and slip rings of conventional generators with brushes [4]. However, rotating rectifier is often prone to over-voltage, over-current and other abnormal factors. According to fault modes, effects and criticality analysis (FMECA) conducted for the brushless AC generator [5], rotating rectifier related faults are one of the most severe electric faults in BASG. In general, the rotating rectifier faults mainly consist of diode open-circuit fault and short-circuit fault. Open-circuit fault is more concerned in particular applications [6]. Generator can still operate safely with a diode open-circuit fault. However, the transient capability of the generator will be limited. If the fault is prolonged, it will have severe influence on generator normal operation [4]. Therefore, unsafe conditions can be avoided and damage to components of the BASG can be minimized by fault detection [7].

Many approaches have been proposed in the literatures for rotating rectifier fault detection in BASG [4]-[9], among these methods, frequency analysis is important. When rectifier diode fails, the original three-phase symmetrical characteristics of the generator are changed, and the harmonic components induced in the exciter generator field winding are also changed [10]. The ac components are also different and, therefore, they become distinguishable for different abnormal conditions. This method is commonly used in practice, but it needs to analyze the harmonic components as the fault features manually.

Based on frequency analysis, this paper presents a fault feature extraction method based on SAE, and this method can be used to BASG rotating rectifier diodes open-circuit fault detection. In this method, exciter generator field current is collected, and processed by FFT to obtain frequency coefficients, and then these coefficients are deeply learned by SAE, which can be viewed as a neural network classifier with deep-learning capability, to extract fault features automatically. The new method can get the intrinsic information (i.e. the fault features) inside the data adaptively and automatically. Fault detection can be easily conducted with Euclidean distance. The experiment results show that, the accuracy of fault detection can reach 100% under different load conditions.

II. THEORETICAL RESEARCH

In this research, a three-stage BASG is considered. The BASG is made up three parts (shown in Fig. 1): permanent magnet generator (PMG), exciter generator, and main generator [11]. Rotating rectifier is located on the rotor between exciter generator and main generator. This part is mainly used to achieve dc field current for main generator.

Four steps are needed for this design, and these steps, shown in Fig. 1, include data acquisition and processing, frequency analysis, feature extraction based on SAE and fault detection.
The authors can achieve $n$ frequency coefficients. The distribution of frequency components has symmetrical characteristics, and the first $n/2$ frequency coefficients are considered in practice. The first coefficient (i.e., dc component) is not used, and actually only $n/2-1$ coefficients are considered. In practice, $n/2-1$ is still a large number for a large $n$. Hence, feature selection needs to be applied to these $n/2$ frequency coefficients for subsequent fault detection [12]. This step is quite difficult for conventional methods, because the features from the considered frequency coefficients are usually selected manually.

### C. Feature Extraction Based on SAE

In this investigation, SAE is adopted as a tool to extract features automatically. SAE is an advanced deep learning neural network. According to our knowledge, feature extraction technique based on SAE in the applications of generator fault detection is seldom addressed in available literatures.

Deep Learning is a group of algorithms that attempt to learn high-level abstractions inside the data by means of deep neural networks (DNNs). SAE is a branch of DNNs, which can learn the intrinsic features from given data and show excellent performance [13].

An auto-encoder is a three-layered neural network that tries to reconstruct the input at the output layer with an hidden layer. Doing this can allow the hidden layer to capture useful higher level representation which can regenerate the input [14]. The typical structure of an auto-encoder is shown in Fig. 3, and it tries to learn a function $F_G(x) \approx x$, where $\theta = \{W, \; b, \; W', \; b'\}$, and $W$ and $W'$ are the weights, $b$ and $b'$ are the biases. An auto-encoder is composed of two parts: encoder and decoder [15], which are shown in Fig. 3.

By applying FFT to each sample which have $n$ data points, the authors can achieve $n$ frequency coefficients. The distribution of frequency components has symmetrical characteristics, and the first $n/2$ frequency coefficients are considered in practice. The first coefficient (i.e., dc component) is not used, and actually only $n/2-1$ coefficients are considered. In practice, $n/2-1$ is still a large number for a large $n$. Hence, feature selection needs to be applied to these $n/2$ frequency coefficients for subsequent fault detection [12]. This step is quite difficult for conventional methods, because the features from the considered frequency coefficients are usually selected manually.

### C. Feature Extraction Based on SAE

In this investigation, SAE is adopted as a tool to extract features automatically. SAE is an advanced deep learning neural network. According to our knowledge, feature extraction technique based on SAE in the applications of generator fault detection is seldom addressed in available literatures.

Deep Learning is a group of algorithms that attempt to learn high-level abstractions inside the data by means of deep neural networks (DNNs). SAE is a branch of DNNs, which can learn the intrinsic features from given data and show excellent performance [13].

An auto-encoder is a three-layered neural network that tries to reconstruct the input at the output layer with an hidden layer. Doing this can allow the hidden layer to capture useful higher level representation which can regenerate the input [14]. The typical structure of an auto-encoder is shown in Fig. 3, and it tries to learn a function $F_G(x) \approx x$, where $\theta = \{W, \; b, \; W', \; b'\}$, and $W$ and $W'$ are the weights, $b$ and $b'$ are the biases. An auto-encoder is composed of two parts: encoder and decoder [15], which are shown in Fig. 3.

By applying FFT to each sample which have $n$ data points, the authors can achieve $n$ frequency coefficients. The distribution of frequency components has symmetrical characteristics, and the first $n/2$ frequency coefficients are considered in practice. The first coefficient (i.e., dc component) is not used, and actually only $n/2-1$ coefficients are considered. In practice, $n/2-1$ is still a large number for a large $n$. Hence, feature selection needs to be applied to these $n/2$ frequency coefficients for subsequent fault detection [12]. This step is quite difficult for conventional methods, because the features from the considered frequency coefficients are usually selected manually.

### C. Feature Extraction Based on SAE

In this investigation, SAE is adopted as a tool to extract features automatically. SAE is an advanced deep learning neural network. According to our knowledge, feature extraction technique based on SAE in the applications of generator fault detection is seldom addressed in available literatures.

Deep Learning is a group of algorithms that attempt to learn high-level abstractions inside the data by means of deep neural networks (DNNs). SAE is a branch of DNNs, which can learn the intrinsic features from given data and show excellent performance [13].

An auto-encoder is a three-layered neural network that tries to reconstruct the input at the output layer with an hidden layer. Doing this can allow the hidden layer to capture useful higher level representation which can regenerate the input [14]. The typical structure of an auto-encoder is shown in Fig. 3, and it tries to learn a function $F_G(x) \approx x$, where $\theta = \{W, \; b, \; W', \; b'\}$, and $W$ and $W'$ are the weights, $b$ and $b'$ are the biases. An auto-encoder is composed of two parts: encoder and decoder [15], which are shown in Fig. 3.
The encoder is a function $f$ that maps an input $x \in X$ to hidden representation $h'$, and the dimension of $h$ is $r$. It has the following form:

$$h' = f_{w,b}(x') = s_f(Wx' + b)$$  \hspace{1cm} (1)

where, $s_f$ is a nonlinear activation function and in our research, Sigmoid function is used as the activation function: $s_f(x) = (1 + e^{-x})^{-1}$ \hspace{1cm} (2)

The decoder function $g$ maps the hidden representation $h'$ to a reconstruction $\hat{x}'$. The expression is as follows:

$$\hat{x}' = g_{w,b'}(h') = s_g(W'h' + b')$$  \hspace{1cm} (3)

where, $W'$ and $b'$ are the weights and biases of the encoder respectively; $s_g$ is the activation function of decoder.

Auto-encoder is trained to find the model parameters $\theta$ by minimizing the reconstruction error on the training set $X$, the corresponding objective function to be minimized is as follows:

$$L(\theta) = \frac{1}{2S} \sum_{x \in X} \| x' - \hat{x}' \|^2$$  \hspace{1cm} (4)

Gradient descent method can serve as an optimization method for getting the minimum of this object function [16].

The above algorithm illustrates learning of weights of a single layer auto-encoder. This technique can also be used to learn weights of a stacked auto-encoder. In learning weights of a stacked auto-encoder with many layers, the network is split layerwise and individual auto-encoders are learned for each layer [17]. The model parameters of stacked auto-encoder can be achieved by the greedy-layer wise unsupervised learning algorithm [14]. SAE can learn fault features from samples automatically, and this process is unsupervised completely [18].

Assume to train $z$ basic auto-encoders, the hidden layer output of the $i^{th}$ ($i=1, 2, ..., z$) auto-encoder is the input of the $(i+1)^{th}$ auto-encoder, and each auto-encoder is trained in the identical way. The hidden layer output of the final auto-encoder is considered to be the fault features.

D. Fault Detection

After the feature extraction, a set of features $X_{feas} = \{x'_{fa} | 1 \leq i \leq S\}$ (where $x'_{fa}$ is the $i^{th}$ feature in $S$ features) can be achieved under healthy condition for the rotating rectifier. The fault detection can be conducted with the following steps:

(i) The center point $C$ for these features need to be calculated with the following form:

$$C = \frac{1}{S} \sum_{i=1}^{S} x'_{fa}$$  \hspace{1cm} (5)

(ii) Calculating the Euclidean distance $D_i$ between the center point and feature points in this set:

$$D_i = \sqrt{E(\hat{x}'_{fa}, C)} , i = 1, 2, ...$$  \hspace{1cm} (6)

where $E(.)$ is the Euclidean function for two vectors. The maximum value $D_{max}$ need to be found:

$$D_{max} = \max_{i=1}^{S}(D_i)$$  \hspace{1cm} (7)

(iii) For an unknown sample $x'$, whose feature sample is $x'_{fa}$ (after FFT and SAE extraction), the Euclidean distance

$$D' = \sqrt{E(x'_{fa}, C)}$$

needs to be computed. Fault detection can be implemented with the following simple form:

$$\begin{cases}
\text{if } D' \leq D_{max} & \text{x' is healthy} \\
\text{if } D' > D_{max} & \text{x' is faulty}
\end{cases}$$  \hspace{1cm} (8)

III. EXPERIMENTAL RESULTS

A test rig has been built to validate the method presented in this paper. The test rig, shown in Fig. 4, is composed of several parts listed in TABLE I. The test rig uses an electric motor (1500 rpm) as the prime mover to drive a three-stage BASG, whose specifications are shown in TABLE II.

In the test rig, for convenience of experiment, the rotating rectifier of the BASG is fixed to the generator body, so the brushes and slip rings are used to connect main field and three-phase exciter armature outputs. Each diode of the rotating rectifier is connected with a switch in series, and open circuit fault can be generated manually.

![Fig. 4. Complete test rig](image)

### TABLE I

<table>
<thead>
<tr>
<th>Number</th>
<th>Name</th>
<th>Type</th>
<th>Manufacturer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Frequency converter</td>
<td>Micromaster</td>
<td>Siemens Co. (Germany)</td>
</tr>
<tr>
<td>2</td>
<td>Electric motor</td>
<td>YVF2-160M4</td>
<td>Siemens Co. (Germany)</td>
</tr>
<tr>
<td>3</td>
<td>Three-stage BASG</td>
<td>YT-7.5-4</td>
<td>Yingtai Co. (China)</td>
</tr>
<tr>
<td>4</td>
<td>Data acquisition system</td>
<td>HS4</td>
<td>Tiepie Co. (Holland)</td>
</tr>
</tbody>
</table>

### TABLE II

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power rating</td>
<td>7.5 kW</td>
</tr>
<tr>
<td>Voltage</td>
<td>400 V</td>
</tr>
<tr>
<td>Speed</td>
<td>1500 rpm</td>
</tr>
<tr>
<td>Frequency</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Poles</td>
<td>4</td>
</tr>
</tbody>
</table>

In this experiment, $f_{i}$f information for several health classes (no-fault, single-diode fault and double-diodes fault)
need to be collected in three load situations (no-load, 1.5KW-load and 3KW load) and the data-sampling rate is 10 KHz. The fault samples (single-diode fault and double-diodes fault) under load conditions are used for testing the method. Fig. 5(a) shows the waveforms of $I_{ef}$ under health condition in three load situations. Fig. 5(b) shows the waveforms of $I_{ef}$ under single diode fault condition in three load situations. Fig. 5(c) shows the waveforms of $I_{ef}$ under double diodes fault condition in three load situations.

Next, FFT is applied to these samples after interception and implements frequency analysis. Altogether 200 FFT coefficients are gained for each sample. By eliminating the dc component, we can get 99 FFT coefficients for each sample. The FFT coefficients (amplitude spectrum) in different load variations under several condition are shown in Fig. 6(a), Fig. 6(b) and Fig. 6(c), respectively. Each coefficient needs to be normalized to [0, 1], and this can avoid large data range.

Fig. 6. The FFT coefficients under three conditions with different loads

For samples interception, the authors choose the waveforms under health condition between 4 complete periods and waveforms between 2 complete periods under each faulty condition, respectively. The collected data points for each sample is 200 ($k=1$, $n=200$). After interception, we can get 600 healthy samples (400 for SAE training and 200 for testing) and 200 faulty samples (for testing purpose). The operation is in the same way for each load situation.

Then, FFT is applied to these samples after interception and implements frequency analysis. Altogether 200 FFT coefficients are gained for each sample. By eliminating the dc component, we can get 99 FFT coefficients for each sample. The FFT coefficients (amplitude spectrum) in different load variations under several condition are shown in Fig. 6(a), Fig. 6(b) and Fig. 6(c), respectively. Each coefficient needs to be normalized to [0, 1], and this can avoid large data range.

Fig. 6. The FFT coefficients under three conditions with different loads

Next, the FFT coefficients are input to a SAE, which has five layers. Input layer for this SAE has 99 nodes (based on the number of features); the first hidden layer has 500 nodes; the second hidden layer has 100 nodes; the third hidden layer has 20 nodes, and output layer has 3 nodes, with which, we can get 3-dimensional features. The numbers of nodes in hidden layers are set empirically. The 3-dimensional features are assumed to be $[\text{fea1}, \text{fea2}, \text{fea3}]$, which needs to be normalized to [0, 1].

The distribution of some selected health and fault Features under different load situations can be illustrated in 3-dimensional space, shown in Fig. 7. The center C (a black circle) of features under health condition is also displayed in Fig. 7. Fault detection can be implemented according to
formula (8) by calculating $D_{\text{max}}$ and the Euclidean distance between unknown feature points and C.

![Diagram](image)

Fig. 7. Features distribution in 3-dimensional space

Under each load situation, altogether 200 samples are used to perform testing of fault detection. The formula of detection accuracy is defined as:

$$\text{acc(\%)} = \frac{N_{\text{cor}}}{N_{\text{tot}}} \times 100$$  \hspace{1cm} (9)

Where, $N_{\text{tot}}$=200 is the number of total test samples for each case, $N_{\text{cor}}$ is the number of correctly classified samples (healthy or faulty) for each case.

Testing results under different cases are given in TABLE III.

<table>
<thead>
<tr>
<th>Load</th>
<th>Healthy</th>
<th>Faulty</th>
</tr>
</thead>
<tbody>
<tr>
<td>No-load</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>1.5KW-load</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>3KW-load</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Testing results in our experiments illustrate that the proposed method is feasible and effective.

IV. CONCLUSION

This paper presents a method of fault feature extraction, which is mainly applied to fault detection of BASGi rotating rectifier. The presented method is based on FFT and deep neural network SAE. The overall steps for features extraction are automatic. Fault detection is simple and high efficient.

The method is implemented and tested using an experimental synchronous generator under different loads and health conditions. Experiment results show that the method is feasible and effective.

V. REFERENCES


VI. BIOGRAPHIES

J. Cui was born in Shandong Province in China on November 23, 1977. He received his Ph.D. degree in Measurement technology and instruments from Nanjing University of Aeronautics and Astronautics (NUAA), Nanjing, China, in 2011. Currently, he is an associate professor at NUAA. His fields of interest include signal processing and applications, circuit diagnosis and prognostics based on machine learning.

J.X. Tang was born in Anhui Province in China on January 26, 1993. He graduated from the Anhui University of Science and Technology, and pursues master degree at NUAA now. His special fields of interest include fault diagnosis.

G. Shi was born in Jilin Province in China on June 23, 1992. She graduated from NUAA and pursues master degree at this school now. Her special fields of interest include fault diagnosis.

Z. R. Zhang was born in Anhui Province in China in 1978. He received the Ph.D. degree in electrical engineering from Nanjing University of Aeronautics and Astronautics (NUAA), Nanjing, China, in 2009. Since 2003, he has been a member of the faculty of the Department of Electrical Engineering, NUAA, where he is currently a Professor. From February 2012 to June 2013, he was a Visiting Professor at the Wisconsin Electric Machines and Power Electronics Consortium, University of Wisconsin–Madison, Madison, WI, USA. His research interests include design and control of permanent-magnet machines, hybrid excitation electric machines, and doubly salient electric machines for aircraft power, electric vehicles, and renewable energy generation.