Fault Detection Method for Permanent Magnet Synchronous Generator Wind Energy Converters Using Correlation Features Among Three-phase Currents

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Abstract—In a permanent magnet synchronous generator (PMSG) system, conversion systems are major points of failure that create expensive and time-consuming problems. Fault detection is usually used to achieve a steady system. This paper presents a full analysis of a PMSG system for wind turbines (WT) and proposes a fault detection method using correlation features. The proposed method is motivated by the balance among the three-phase currents both before and after an open-circuit fault occurs in a converter of the PMSG system. It is unnecessary to analyze the output waveforms of a converter during fault detection. In this study, two correlation features of statort currents, the mean and covariation, are extracted to train an artificial neural network (ANN), thereby enhancing the performance of the proposed method under different wind speed conditions. Moreover, additional sensors and the collection of a massive amount of data are not required. Model simulations of an ideal inverter and a PMSG system are conducted using PSCAD software. The simulation results show that the proposed method can detect the locations of faulty switches with a diagnostic rate greater than 99.4% for the ideal inverter, and the PMSG drives settings at different wind speeds.

Index Terms—Permanent magnet synchronous generator (PMSG), artificial neural network (ANN), mixed logical dynamical (MLD) theory, conversion system.

I. INTRODUCTION

RECENTLY, wind power has become an option to alleviate environmental problems because it is a clean and infinite energy source. The permanent magnet synchronous generator (PMSG) is a promising technology for wind power integration. Full-scale power converters along with PMSGs have been in high demand for tracking variable wind speeds and for fulfilling rigorous grid requirements [1]. However, faults are inevitable in any system [2]. The highest failure rate in power electronic modules is reported to be 32% [3]. It is claimed that the failures are mainly caused by defective semiconductors [4]. Furthermore, many factors such as accidental overcurrent, high electrical and thermal stress, bonding wire lifting by thermal cycling, fuse failure protection, and gate command signal failures, may cause open-circuit faults (OCFs) in one or more switches [5]. Fault events in power converters may damage electrical energy flow, threaten power system safety as well as harm humans and the environment [2], [3].

Failures in power converter devices usually occur in the form of OCFs or short-circuit faults. Devices that protect against overcurrent and short circuit are considered as important standard components of industrial drives [6]. Slow responses to OCFs may not trigger overcurrent protection, but drive performance would be degraded. The potential secondary faults could lead to the malfunctioning or damage of other components due to noise and vibration, which would cause the PMSG to shut down. Maintenance costs have been reported to be 13% of the total cost [4]. Therefore, efficient and effective fault detection is very important.

Diagnostic techniques remain a popular topic in the literature [7], [8]. According to the types of estimated fault signals, detection techniques can be categorized into voltage-based methods and current-based methods [9]. Compared with current-based methods, voltage-based methods detect faulty switches in less time and with lower sensitivity to wind speed, but they are more expensive and require additional space to accommodate for hardware [10]. In contrast, current-based methods do not require additional sensors.

Current-based methods have been investigated for various electric machines and drives for years [9]. A previous analysis of the output waveforms has shown that faults can be detected using features such as the mean current [11], the normalized DC [12], the D-Q current [13], and the current vector trajectory [14]. The D-Q current can be distorted due to current measurement noise, converter dead-time, and harmonics [10]. This distortion can reduce the fault detection performance [15]. Meanwhile, the current vector trajectory method can be used to detect faults in PMSGs drivers under no-load or light-load conditions [14]. However, the current is sensi-
tive to many factors such as uncertainty, noise, and load changes. If the detection methods are designed using features obtained from the output waveforms of the currents, then the performance can be degraded due to the high sensitivity of the current.

To resolve this sensitivity, large amounts of data and time are needed [7]. For instance, handling deviation data is very time-consuming [9]. Despite enhanced robustness, the calculation of the parameters (e.g., second harmonic, high-order harmonics) is highly demanding in terms of software resources [6], [16]. An artificial neural network (ANN) trained by the features extracted from motor currents and the DC-link current has been applied to detect and identify fault locations [17]. An adaptive self-recurrent wavelet ANN has provided an estimation of a nonlinear model for generating the appropriate fault indicators [18].

Some articles have indicated reliability issues for power electronic detection methods [2], [19]. To improve the reliability, this study proposes a correlation feature identification method. The features are extracted by considering the balance among the three-phase currents. Analysis of the output waveforms of converters is avoided, and the collection of a massive amount of data is unnecessary. The paper is organized as follows: Section II focuses on the investigation of faulty behaviors, and the influences of a closed-loop converter control strategy on the behaviors of the PMSG. Section III presents the identification method for OCFs, while section IV describes the model simulations of an ideal inverter and a PMSG system conducted using PSCAD. The results show that the ANN fault detection method using correlation features can detect OCFs in both single and double switches for PMSG drives at different wind speeds.

II. INVESTIGATION OF FAULTS IN MOTOR-SIDE CONVERTER

A. Normal Condition

First, certain simplifying assumptions are made. The switches of the converter are ideal, and their power loss and resistance are equal to 0. The back trapezoidal electromotive force (EMF) of generator $e_{0s}$, the phase stator resistance $R_{ks}$, and the phase stator inductance $L_{ks}$ ($k = a, b, c$) are the parameters of the generator. They were connected in series at each phase to obtain the PMSG model. Figure 1 shows the equivalent circuit of the PMSG system [20], constrained by $e_{0s}$ and the stator current $i_k^s$ ($k = a, b, c$), as shown in (1).

$$\begin{align*}
    e_{as} + e_{bs} + e_{cs} &= 0 \\
    i_{as}^s + i_{bs}^s + i_{cs}^s &= 0
\end{align*}$$

(1)

From Fig. 1, using Kirchhoff’s voltage law, we obtain:

$$\begin{align*}
    L_{as} \frac{di_{as}^s}{dt} + R_{as} i_{as}^s &= u_{as} - e_{as} \\
    L_{bs} \frac{di_{bs}^s}{dt} + R_{bs} i_{bs}^s &= u_{bs} - e_{bs} \\
    L_{cs} \frac{di_{cs}^s}{dt} + R_{cs} i_{cs}^s &= u_{cs} - e_{cs}
\end{align*}$$

(2)

where $u_{as}$ ($k = a, b, c$) is the stator voltage. The switching function is determined by the values of the three-phase gate command signals, i.e., $s_a$, $s_b$, and $s_c$. For example, if the gate command signal of phase A $s_a$ is equal to 1, then T1 is ON; if $s_a$ is equal to 0, then T4 is ON. The stator currents $i_k^s$ flowing into the windings are defined as positive.

![Fig. 1. Equivalent circuit of PMSG system.](image)

The current direction and switching signal determined the values of the lower tube voltage $u_{ks}$ ($k = a, b, c$), which can be expressed by:

$$
    u_{ks} = s_k u_{dc}, \quad k = a, b, c
$$

(3)

where $u_{dc}$ plus the $N$ to neutral voltage $u_{ks0}$ equals $u_k$ ($k = a, b, c$). The sum of the three equations in (2) provides the mathematical expressions of $u_{ks0}$ and $u_{ks}$ as follows:

$$\begin{align*}
    u_{s0} &= -\frac{1}{3} (s_a + s_b + s_c) u_{dc} \\
    u_{s0} &= \frac{1}{3} (2s_a - s_b - s_c) u_{dc} \\
    u_{s0} &= \frac{1}{3} (2s_b - s_a - s_c) u_{dc}
\end{align*}$$

(4)

The other constraint relationship is deduced as:

$$u_{sd0} + u_{sb0} + u_{sc0} = 0$$

(6)

This relationship is verified in [21]. Thus, the vector control rules are as follows:

$$u_k = u_{k0} + u_{k0} e^{j\zeta} + u_{k0} e^{j(\zeta + \frac{2\pi}{3})} \quad \zeta = \frac{2\pi}{3}$$

(7)

where $u_k$ is the voltage control variable. The rules, shown in Fig. 2, are calculated as in Appendix A.

![Fig. 2. Vector control schematic.](image)
B. Fault Conditions

In practice, a power switch comprises two main parts: an insulated-gate bipolar transistor (IGBT) and a parallel freewheel diode (PFD). Power switch faults caused by gate drive failures easily lead to OCFs in the motor side converter (MSC) [22]. In this case, the PFD remains connected to the MSC, even though its parallel connected switch is open. The behaviors of the fault events for single switches have received much attention. Nonetheless, our main concern is the behaviors of multiple OCFs, and we focus on the research of T5T6 faults as an example.

Figure 3 shows the basic configurations for T5T6 faults. In Fig. 3(a), the lower tube voltage of phase A $u_{N3}$ is determined by the stator current $i_s$ and the gate command signals $s_{cc}$ of phase A, as in the normal conditions. The operation of the IGBTs and diodes in phase B is shown in Table I.

![Switching model of three legs in the event of T5T6 faults.](a) Phase A. (b) Phase B. (c) Phase C.]

![Fig. 3. Switching model of three legs in the event of T5T6 faults.](a) Phase A. (b) Phase B. (c) Phase C.]

**TABLE I**

| $i_s^c$ | $s_{cc} = 1$ | $s_{cc} = 0$ |
|---------|-------------|-------------|
| $i_s^c > 0$ | $T3 \text{ ON}, \ u_{N3} = u_{dc}$ | $VD6 \text{ ON}, \ u_{N3} = 0$ |
| $i_s^c < 0$ | $T3 \text{ ON}, \ u_{N3} = u_{dc}$ | $VD3 \text{ ON}, \ u_{N3} = u_{dc}$ |

Therefore, the stator current of phase B $i_s^c$ can flow bilaterally, and the lower tube voltage of phase B $u_{N3}$ can be expressed by (8).

\[
\begin{align}
  u_{N3} &= \begin{cases} 
    0 & i_s^c > 0 \\
    u_{dc} & i_s^c < 0 \text{ or } s_{cc} = 1 
  \end{cases}
\end{align}
\]

By analyzing Fig. 3(c), we obtain the following:

\[
\begin{align}
  u_{N3} &= \begin{cases} 
    0 & i_s^c > 0 \\
    u_{dc} & i_s^c < 0 \text{ and } s_{cc} = 1 
  \end{cases}
\end{align}
\]

The mixed logical dynamical (MLD) theory is one approach used for modeling the hybrid system. In accordance with the MLD theory, we define the auxiliary logic variables ($\delta_{dc}$, $\delta_i$). We set $\delta_{dc} = 1$ for $i_s^c > 0$, and $\delta_{dc} = 0$ for $i_s^c < 0$. A similar logic relationship applies for $\delta_i$ and the stator current of phase C $i_s$. Thus, in the event of T5T6 faults, $u_{N3}$ can be described as:

\[
\begin{align}
  u_{N3} &= s_{cc} u_{dc} \\
  u_{N3} &= (\delta_{dc} s_{cc} + \delta_i) u_{dc} \\
  u_{N3} &= \delta_i s_{cc} u_{dc}
\end{align}
\]

Using (1) and (6), we can deduce $u_{dc}$ and $u_{dc}$ as follows:

\[
\begin{align}
  u_{N0} = -\frac{1}{3} \left( s_{cc} + \delta_{dc} s_{cc} + \delta_i + \delta_i s_{cc} \right) u_{dc} \\
  u_{N0} = \frac{1}{3} \left( 2s_{cc} - \delta_{dc} s_{cc} - \delta_i - \delta_i s_{cc} \right) u_{dc} \\
  u_{N0} = \frac{1}{3} \left( -s_{cc} + 2\delta_{dc} s_{cc} + 2\delta_i - \delta_i s_{cc} \right) u_{dc} \\
  u_{N0} = \frac{1}{3} \left( -s_{cc} - \delta_{dc} s_{cc} - \delta_i + 2\delta_i s_{cc} \right) u_{dc}
\end{align}
\]

The results in Appendix B can be deduced according to (12). The vectors are controlled as shown in Fig. 4 in the event of T5T6 faults. The direction of $i_s^c$ affects the vector control rules. These control rules are not the only ones in the event of T5T6 faults. Different $\delta_{dc}$ values are obtained by comparing (5) with (12). Additionally, the values of $i_s^c$ differ. More specifically, the electrical signals of the PMSG system are affected by the occurrence of OCFs.

The analysis of the fault modes reveals that bidirectional passageways exist for stator currents in the event of an OCF. Faults disrupt the vector control normal rules. Meanwhile, the new control rules are dependent on both the current and the voltage. The current and the voltage are also affected by the occurrence of OCFs. A strong coupling relationship exists between the control rules and the electrical signals.

C. Closed-loop Control Strategy

In general, the control strategy for MSC includes two closed loops: the speed loop and the flux loop [23]. The complete block diagram is shown in Fig. 5, where $\omega$ and $\omega_c$ are the actual rotor speed and the reference rotor speed, respectively; and $h$, $f$, and $g$ denote the functional relations of the PWM controller, the PID controller, and the rotor speed controller, respectively.

**Fig. 4.** Vector control schematic diagram in the event of T5T6 faults. (a) $\delta_{dc} = 1$, $\delta_i = 0$. (b) $\delta_{dc} = 0$, $\delta_i = 1$. (c) $\delta_{dc} = \delta_i = 1$. (d) $\delta_{dc} = \delta_i = 0$.

The speed loop is achieved through the error $e_\omega = \omega - \omega_c$.
suitably regulated by the rotor. The flux control strategy is achieved through $x$, an electrical parameter; for example, $i'_s$ is the active power. This parameter is applied to calculate the optimal control voltage in the next step [23]. As in conventional approaches, the $s_i$ values are provided by the PWM controller. Therefore, $s_i$ can be written as:

$$s_i = \frac{h\left(x - g(\omega - \omega_0)\right)}{h}$$  \hspace{1cm} (13)

According to the relationship in (13), $\omega$ and $x$ affect the values of $s_i$. However, various rotor speeds are easily produced due to the changes in wind speed. Thus, $x$ such as $i'_s$ is also sensitive to the operation mode. As a consequence, different values of $s_i$ are obtained for different arrangements. Substituting (13) into (2), the generator functions can be expressed as:

$$\begin{align*}
L_\omega \frac{di'_a}{dt} + R_\omega i'_a &= u_s \left(h\left(x - g(\omega - \omega_0)\right), u_a\right) - e_{\omega a} \\
L_\omega \frac{di'_b}{dt} + R_\omega i'_b &= u_s \left(h\left(x - g(\omega - \omega_0)\right), u_b\right) - e_{\omega b} \\
L_\omega \frac{di'_c}{dt} + R_\omega i'_c &= u_s \left(h\left(x - g(\omega - \omega_0)\right), u_c\right) - e_{\omega c}
\end{align*}$$  \hspace{1cm} (14)

For convenience of expression, $u_a$, $u_b$, and $u_c$ represent the functions of $u_{\omega a}$, $u_{\omega b}$, and $u_{\omega c}$, respectively.

$$\begin{align*}
L_\omega \frac{di'_a}{dt} + R_\omega i'_a &= u_a \left(s_1, u_a\right) - e_{\omega a} \\
L_\omega \frac{di'_b}{dt} + R_\omega i'_b &= u_b \left(s_1, u_b\right) - e_{\omega b} \\
L_\omega \frac{di'_c}{dt} + R_\omega i'_c &= u_c \left(s_1, u_c\right) - e_{\omega c}
\end{align*}$$  \hspace{1cm} (15)

We assume that different fault modes such as an OCF in two switches or in a single switch, occur in the MSC. As the analysis in Section II-B indicates, different fault modes result in different electrical signals. We assume that $u_{\omega 01}$ and $u_{\omega 02}$ are produced in two different fault modes. Therefore, the generator functions can be expressed by:

$$\begin{align*}
L_\omega \frac{di'_a}{dt} + R_\omega i'_a &= u_{\omega 01} - e_{\omega a} \\
L_\omega \frac{di'_b}{dt} + R_\omega i'_b &= u_{\omega 02} - e_{\omega b}
\end{align*}$$  \hspace{1cm} (16)

If the circuit topology and the control strategy are fixed, constrained relationships among the three-phase currents and voltages given in (16) exist. The instantaneous values should be different in the above two conditions. The above analysis proves that the system is strongly coupled. Many factors such as the wind speed and operation mode, influence the electrical signals. Their distortions are nonlinear.

**D. Distortion of Stator Current**

Experiments and simulations are conducted to verify the nonlinear distortion of the stator current [24]. The main parameters of the PMSG system are given in Table II. Model simulations of the PMSG system are carried out using PSCAD. The main system parameters are given in Table III. The model is simulated at a wind speed of 10.5 m/s. The dynamic responses of $i'_s$ are shown in Fig. 7. The curves shown in Fig. 7 are all bidirectional. The enve-
lapses of the curves are still trigonometric functions. We investigate these curves, as shown in Fig. 7(b) and (c). These two curves are obtained during a T4 fault and a T1 fault, respectively. The currents distort nonlinearly with little variation. If other arithmetical operations or transformations are not added, then it is difficult to distinguish the faulty switch by the current curves. Similar characteristics between the simulations and experiments are obtained. These similar characteristics also prove that the simulation model is effective and applicable.

![Image of curves](image.png)

**Fig. 7.** Simulation results regarding stator currents. (a) Normal operation condition. (b) Operation condition during T4 fault. (c) Operation condition during T1 fault.

To describe the behaviors, the information on residuals and D-Q currents are illustrated in Figs. 8 and 9, respectively. In Fig. 8(a) and (b), the three-phase residuals are generally not equal to 0. Thus, the \( \bar{i}_q \) curves are distorted most of the time. The curves are hard to express via mathematical functions. The distortions of the \( \bar{i}_q \) curves are nonlinear. In Fig. 8(b), the residual of phase A is positive most of the time. However, as in Fig. 8(c), in the T1 fault condition, the main trend of the residual of phase A is negative. This response is consistent with that in [12]. According to the residuals during the T1 and T4 faults, we can deduce that the mean currents vary in these two fault conditions.

The system is constrained as shown in (2). In view of this, we can deduce that the residual sums equal 0. To verify this deduction, the residual sums are calculated. The curves shown in Fig. 8(c) are restricted to be close to 0. Therefore, the fact that a dynamic balance always exists among the three phases regardless of fault modes is proven.

The waveforms of the D-Q currents are plotted in Fig. 9. The shapes in the two subgraphs are both circles. These results also prove that the \( \bar{i}_q \) curves are bidirectional.

![Image of waveforms](image.png)

**Fig. 9.** Waveforms of D-Q currents. (a) T1 fault condition. (b) T4 fault condition.

The results prove the dynamic faulty behaviors in the event of a T1 or T4 fault. The distortions of the \( \bar{i}_q \) curves are nonlinear. The shapes of the D-Q current figures are circular. Meanwhile, the three-phase stator currents maintain a dynamic balance.

Considering these investigations, we can draw the follow-
ing conclusions. The vector control rules are affected by the current directions. A bidirectional stator current can flow through the MSC in the event of an OCF. A strong coupling relationship exists between the electrical signals and gate command signals. The shapes of the D-Q current figures are circular. Moreover, the distortion of the stator current is nonlinear, but the three-phase currents maintain a dynamic balance.

III. ALGORITHM FOR DIAGNOSTIC PROCEDURE

Because of the strong coupling and nonlinear features, the fault features of the stator current are hard to express via mathematical functions in the event of an OCF. An ANN has many merits for nonlinear system detection. The stator current can also be obtained without extra sensors. Therefore, we design the diagnostic method shown in Fig. 10, where 

\[ I = \frac{1}{N} \sum_{n=0}^{N-1} i_n \]  

is the mean current in a period. The detection method includes four steps: sampling, smoothing, and feature extraction and detection by the trained ANN. Generally, the MSC is regulated by the stator smoothing, and feature extraction and detection by the ANN. Before the application of RBF ANN, 

\[ \rho = \frac{1}{360} \sum_{i=0}^{n} r_i^2 \rho \]  

where \( \rho = \rho_{i+1} - \rho_i \) is the central angle; \( r_i = \sqrt{r_{d,i}^2 + r_{q,i}^2} \) is the radius; \( n \) is the total number for the division of the total surface; \( r_{d,i} = 0.5(i_{d_{\max}} + i_{d_{\min}}) \) and \( r_{q,i} = 0.5(i_{q_{\max}} + i_{q_{\min}}) \); and \( \theta_{\max} \) and \( \theta_{\min} \) are the maximum and minimum values of the current measured during one period, respectively. The features in (19) express the three main elements of a signal, which is the main reason why we chose these features for detection. These features also show the D-Q current trajectory feature. Therefore, the first type of feature is the D-Q current trajectory feature.

The output waveform analysis of converters is the key to most of the current-based detection methods. The second type of feature is extracted by the output waveform analysis of converters. Two features, i.e., \( I_k \) and the mean square error in each half period \( (I_{kh}I_{kh}) \), are extracted. The former has been proven useful for single fault detection in many studies. The idea of extracting the mean square error in each half period is motivated by Section II-B. Furthermore, the vector control rules are affected by the current direction. With this in mind, we use the mean square error in each half period for detection. These errors can be expressed as follows:

\[ I_{kh} = \sqrt{\frac{1}{7} \sum_{i=0}^{7} (i_{kh} - I_{kh})^2} \]  

\[ I_{dh} = \sqrt{\frac{1}{7} \sum_{i=0}^{7} (i_{dh} - I_{dh})^2} \]
where \( k = a, b, c \); \( \bar{I}_a \) and \( \bar{I}_b \) are the averages in the first and second half of each period, respectively; and \( \bar{I}_a, \bar{I}_b, \) and \( \bar{I}_c \) correspond to the three-phase current vector amplitude features, respectively. Therefore, we call the second type of feature the three-phase current trajectory feature.

Due to the strong coupling and nonlinear features of the PMSG system, it is difficult to express the current distortions via mathematical functions. Although the distortions of the stator current are nonlinear, the three-phase currents maintain a dynamic balance. This conclusion is deduced in Section II. Therefore, we attempt to extract the correlation features for detection. The considered correlation features comprise two parts: a self-correlation feature and a cross-correlation feature. In general, the stator current has symmetrical characteristics. To save calculation time, we use the means \( \bar{I}_a \) to replace the variance in each phase as the self-correlation feature. The cross-correlation feature is extracted based on the covariances \( C \) calculated by:

\[
\begin{align*}
C_{aa} & = \frac{1}{m-1} \sum (i_a - \bar{I}_a)(i_a - \bar{I}_a) \\
C_{ab} & = \frac{1}{m-1} \sum (i_a - \bar{I}_a)(i_b - \bar{I}_b) \\
C_{ac} & = \frac{1}{m-1} \sum (i_a - \bar{I}_a)(i_c - \bar{I}_c)
\end{align*}
\]

(21)

The correlation features are not obtained by analyzing the output waveforms of the converters. The means reflect the correlation features in each phase, while the covariances show the correlations between two phases.

C. Methodology of ANN Fault Classification

The ANN is defined as an RBF network to detect faults.

The OCF modes are divided into three types: F1, F2, and F3. F1 corresponds to faults in one faulty switch such as T1, T2, T3, T4, T5, and T6 faults. Two-switch faults are classified as F2, including T1T2, T1T3, T1T4, T1T5, T1T6, T2T3, T2T4, T2T5, T2T6, T3T4, T3T5, T3T6, T4T5, T4T6, and T5T6 faults, corresponding to 15 fault patterns. F3 contains all faults of both F1 and F2. To produce an OCF, the gate signals corresponding to different fault modes are

IV. IMPLEMENTATION OF RBF ANN DIAGNOSTICS

Considering the damage to devices, we have tested the detection method using a simulation model. A computer simulation program has been developed using PSCAD. The closed-loop controlled PMSG drives and ideal inverter are set up to verify the performance of the proposed method. The ideal converter and PMSG drives are shown in Figs. 11 and 12, respectively. The RRL model indicates the transmission line (its impedance form is \( R-R/L \)). The system parameters of the PMSG drives are listed in Table III. The effectivity and applicability of the simulation model are verified in Section II-C.

The OCF modes are divided into three types: F1, F2, and F3. F1 corresponds to faults in one faulty switch such as T1, T2, T3, T4, T5, and T6 faults. Two-switch faults are classified as F2, including T1T2, T1T3, T1T4, T1T5, T1T6, T2T3, T2T4, T2T5, T2T6, T3T4, T3T5, T3T6, T4T5, T4T6, and T5T6 faults, corresponding to 15 fault patterns. F3 contains all faults of both F1 and F2. To produce an OCF, the gate signals corresponding to different fault modes are
moved. By collecting all fault states for the simulations, we extract 50 samples of each fault mode at three wind speeds: the cut-in wind speed (6 m/s), the cut-out wind speed (15 m/s), and a middle speed (9 m/s). Additionally, a dataset is collected for the ideal converter. These four datasets are used to train the RBF ANN. Therefore, the training number of samples for the RBF is $50 \times 21 \times 4 = 4200$ (i.e., 50 periods, 21 fault modes, and 4 conditions).

Here, we have listed only the features of the PMSG drives. The waveforms of the means are plotted in Fig. 13. All features expressed in (19)-(21) in the 21 different fault modes are shown in Figs. 14-16. The waveforms in Fig. 13 show that most values of the means are not equal to 0. Figure 14 shows the covariations with huge differences in the various fault modes. We compared the 3 subgraphs in Fig. 14. According to the three covariation curves, different faults have different dynamic features.

![Fig. 13. Waveforms of mean currents in PMSG drives.](image)

![Fig. 14. Waveforms of covariations.](image)

The current amplitudes are disclosed by the mean square errors plotted in Fig. 15. In the same fault mode, $I_{a15}$, $I_{a16}$, $I_{a17}$, $I_{a18}$, $I_{b16}$, and $I_{c16}$ are different. Different fault modes lead to distinct mean square errors, which correspond to 6 parameters. The 6 parameters should be computed in each half period. The covariations correspond to 3 parameters. The computations are conducted in each period. Therefore, the number of operations for the mean square errors is more than that for the covariations. Moreover, only the amplitudes are reflected by the mean square errors. The frequency and phase angle are not recorded. Therefore, a three-phase current trajectory may be incompletely drawn.

The D-Q current features are depicted in Fig. 16. Even with varying fault modes, $S$ and $\theta$ seem fairly stable. These two features may be invalid for distinguishing faults. The values of $\phi$ change in different fault modes. Therefore, we hypothesize that the robustness of the D-Q ANN-based method may be low. Moreover, the calculation process of the D-Q current features requires a comparison using a high level of computing resources. These features are obtained after the D-Q transform.

All fault states are detected by the proposed detection method. We initially set the wind speed to 7 m/s and then increased it to 10.5 m/s. In each wind speed condition, 21 typical faults occur in a six-switch converter. These 21 faults are single-switch faults and two-switch faults. In one condition, each fault lasts for 4 s, then recovers. Between the two fault modes, a period of 3 s elapses to allow the system to stabilize. A total of $60 \times 21 \times 3 = 3780$ samples are detected by the trained ANN. These samples with 21 fault modes are ob-
tained in 3 different conditions: an ideal inverter, a PMSG drive with a wind speed of 7 m/s, and a PMSG drive with a wind speed of 10.5 m/s. Each fault mode include 60 cycles. We have tested the proposed method in 12 different fault conditions, classified by model, wind speed, and OCF type, as shown in Table IV.

Fault detection for the ideal converter is achieved by all three types of RBF ANNs. For the PMSG wind system, the correlation ANN and three-phase ANN can distinguish single faulty switches with a 100% diagnostic rate regardless of the wind speed. However, the maximum diagnostic rate of the D-Q ANN is 66.03%. The D-Q ANN is also implemented in [16]. A similar feature between the model in [16] and the ideal converter is that the stator current in the fault phase is unidirectional.

With reference to Table IV, the diagnostic rate of the three-phase ANN is only 73.30% for F2. The three-phase ANN appears to be sensitive to the wind speed. We chose samples to test the three-phase NNW in the fault mode. Five types of fault patterns, i.e., T3T5, T3T6, T4T5, T4T6, and T5T6 faults, could not be identified when the wind speed is 10.5 m/s. The correlation ANN shows a higher diagnostics rate, up to 99.4%, than the other ANNs. Additionally, the correlation ANN can classify all faults. To understand the main advantages and disadvantages of the three types of ANNs, a comparison is conducted, as shown in Table V.

### Table IV
**Simulation Results**

| Model       | Wind speed (m/s) | OCF type | Fault pattern | Diagnostic rate (%) |
|-------------|-----------------|----------|---------------|---------------------|
| Ideal inverter | Fixed           | F1       | 6             | 100.0              |
|             |                 | F2       | 15            | 100.0              |
|             |                 | F3       | 21            | 100.0              |
| PMSG driver  | 7.0             | F1       | 6             | 100.0              |
|             |                 | F2       | 15            | 100.0              |
|             |                 | F3       | 21            | 100.0              |
|             | 10.5            | F1       | 6             | 100.0              |
|             |                 | F2       | 15            | 100.0              |
|             |                 | F3       | 21            | 100.0              |
| Both        | F1              | 6        | 100.0         |
| Both        | F2              | 15       | 100.0         |
| Both        | F3              | 21       | 100.0         |

### Table V
**Comparison Among Three Types of ANNs**

| Method       | Analysis of output waveform | Speed of features extraction | Scope of application |
|--------------|-----------------------------|-----------------------------|----------------------|
| D-Q ANN      | Necessary                   | Slowest                     | Yes                  |
| Three-phase  | Necessary                   | Middle                      | Yes                  |
| Correlation ANN | Unnecessary               | Fastest                     | Yes                  |

The correlation ANN without analysis of the output waveform is based on the balance of three-phase currents. Therefore, the correlation feature fault detection method has strong robustness and is useful for various converters. In addition, the correlation features are extracted, not from the D-Q current, but from the three-phase currents directly, which helps shorten the sampling time. The correlation ANN has more advantages than the other two types of ANNs.

Overall, the fault detection method using correlation features can identify the location of faulty switches regardless of the wind speed. The three-phase ANN can distinguish all fault modes in the ideal inverter but is sensitive to the wind speed when applied to the PMSG system. Meanwhile, the D-Q ANN is only suitable for diagnosing the ideal inverter.

### V. Conclusion

We have proposed a fault detection method using the correlation features for the PMSG drives in a wind power system in this paper. The analysis of the output waveform of converters is avoided. The extracted features are obtained from the constraint relationship between the three-phase circuits. The results show that the robustness is enhanced by the proposed approach.

Using a small amount of sampling data and a short calculation time, features are extracted from three-phase currents by simple addition and subtraction without complex calculations such as the Park translation or FFT.

The high performance of the correlation feature method is verified through the results. The proposed detection method based on the balance of three-phase currents is a novel meth-
od. Generalizing the approach to other types of faults will be considered as the following work for engineering implementation in the future.

**APPENDIX A**

The control rules of vector voltages are given in Table A1.

### APPENDIX B

If $\delta = 1$ and $\delta = 0$, then

$$
\begin{align*}
    u_{ab} &= \frac{1}{3} (2s_a - s_b - s_c) u_{dc} \\
    u_{b0} &= \frac{1}{3} (-s_a + 2s_b - s_c) u_{dc} \\
    u_{c0} &= \frac{1}{3} (-s_a - s_b + 2s_c) u_{dc}
\end{align*}
$$

Therefore, $u_{c0}$ is the same as in Appendix A.

If $\delta = 1$ and $\delta = 1$, then

$$
\begin{align*}
    u_{ab} &= \frac{1}{3} (2s_a - s_b - s_c) u_{dc} \\
    u_{b0} &= \frac{1}{3} (-s_a + 2s_b - s_c) u_{dc} \\
    u_{c0} &= \frac{1}{3} (-s_a - s_b + 2s_c) u_{dc}
\end{align*}
$$

If $\delta = 0$ and $\delta = 0$, then

$$
\begin{align*}
    u_{a0} &= \frac{1}{3} (2s_a - 1 - s_c) u_{dc} \\
    u_{b0} &= \frac{1}{3} (-s_a + 2 - s_c) u_{dc} \\
    u_{c0} &= \frac{1}{3} (-s_a - 1 + 2s_c) u_{dc}
\end{align*}
$$

If $\delta = 0$ and $\delta = 1$, then

$$
\begin{align*}
    u_{a0} &= \frac{1}{3} (2s_a - 1) u_{dc} \\
    u_{b0} &= \frac{1}{3} (-s_a + 2) u_{dc} \\
    u_{c0} &= \frac{1}{3} (-s_a - 1) u_{dc}
\end{align*}
$$

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