Open-switch fault diagnosis in voltage source inverters of PMSM drives using predictive current errors and fuzzy logic approach

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Abstract
In critical industrial applications fault diagnosis and fault tolerance are considered key features, in order to ensure the required reliability and availability levels. In this context, this paper proposes a new and effective diagnostic algorithm for power semiconductors open-circuit faults, in three-phase, two-level, voltage-source inverter-fed permanent magnet synchronous machine (PMSM). The proposed method is based on the analysis of the errors between the reference currents and the PMSM stator predictive currents. Hence, for each phase of the PMSM two fault diagnostic variables have been defined, which allow the diagnosis of both single and multiple open-circuit faults. The fuzzy logic approach is applied to the fault diagnostic variables in order to identify the faulty power switches. The method is experimentally validated on a model predictive controlled (MPC) permanent magnet synchronous motor (PMSM) drive, which shows the effectiveness of the fault diagnosis algorithm with a high robustness regarding the operating point and parameter variations of the PMSM drive system.

1 INTRODUCTION

Permanent magnet synchronous motor (PMSM) drives have been widely used in many industrial applications, such as electric traction, aircraft, robotics, medical equipment, and servo mechanisms. Indeed, they are preferred, in many applications, due to their high efficiency, high torque-to-inertia ratio, high power factor, faster response, and rugged construction.

The overall performance of any drive system is extremely dependent on the reliable functioning of all of its components. Failure of any one of its components may lead to severe losses in terms of productivity and capital gain. Hence, drive systems fault diagnosis is, nowadays, an important area of research. Variable speed drives fed by voltage source inverters (VSIs) are subject to several types of faults, such as: inverter faults, machine faults, and sensors faults. Inverter faults include, in general, DC link capacitors and power switches (open- or short-circuit) faults [1].

As power switch faults deteriorate the VSIs’ performance, the diagnostics of such faults is mandatory. The state-of-the-art review shows that several approaches have been focused on the diagnosis of short-circuit and/or open-circuit faults in VSIs [1, 2].

Since a short-circuit fault is an instantaneous destructive fault, additional hardware circuits for fault diagnosis are usually employed [2]. Regarding open-circuit fault diagnosis, the state-of-the-art review shows that the proposed approaches are classified into [3]:

Model-based methods.
Signal-based methods.

Model-based and signal-based methods are also subdivided into voltage-based or current-based algorithms. Model-based open-circuit fault diagnosis algorithms require the use of observers [4–18]. The fault diagnosis process is generally achieved through residual generation. Some contributions have proposed observers to estimate motor or grid currents [4–9] whereas others have been dedicated to estimate converter’s output voltages [10–18]. For current-based algorithms, a residual is generated by comparing the measured current with the observed current. Several observers have been proposed such
as: state estimators [4, 5], Luenberger observers [6], proportional integral (PI) observers [7], sliding mode observers [8], and Kalman filter [9]. In case of voltage-based approaches, and in order to avoid the use of additional sensors, the residual results from the comparison of the estimated voltage with the reference voltage obtained from the feedback control. Generally, state estimators are employed [10–16], but PI and model reference adaptive system (MRAS) observers have been also proposed in [17] and [18], respectively.

Model-based algorithms have shown good performance in terms of robustness and fault detection time. However, as main drawbacks, they are computationally demanding, needing high tuning efforts for the observer parameters design, and requiring the knowledge of the machine parameters.

Signal-analysis-based methods have been also proposed to achieve open-circuit fault diagnosis. The main advantage of this approach is that it is free from system’s model knowledge. They may be classified into three different groups: current Park’s vector approaches, Normalized current average value approaches, data driven and artificial intelligence approaches. As for the model-based approaches case, converter’s currents as well as voltages’ signatures have been investigated.

The use of the Park’s vector approach (PVA) as a fault diagnostics technique for VSI faults was successfully applied in [19–22]. Bae et al. [21] discussed a fault detection and identification approach by monitoring the dwell time of each voltage sector obtained from measured and reference currents. Then after, the faulty switch(es) is (are) identified by analysing the line-to-line motor currents variation. In [22], the detection and localisation of an open-phase fault in three-phase induction motor drives through the second order rotational Park’s transformation is addressed.

The normalized current average value approach has been later proposed to ensure an effective open-circuit fault diagnosis in AC machine drives [20, 23–25]. In [23], Yan et al. propose the use of a single DC current sensor for the reconstruction of the motor stator currents. The reconstructed currents are then employed to achieve open-circuit fault diagnosis, through the currents’ average values variation. In [24], the authors use only the measured currents signals, and the combination of two fault indicators, to diagnosis a total of 27 open-circuit faults and three current sensor faults. This approach has the merit to be useful for closed-loop control as well as open-loop control of AC drives but needs quite high computational resources for real time implementation. Jlassi et al. [25] presented a mixed approach using the current Park’s vector approach and normalized current average value approach for the diagnosis of multiple types of faults in regenerative PMSM drives. The proposed algorithm is able to diagnose IGBT faults, current sensor faults, and speed sensor faults.

Power switch open-circuit fault diagnosis based on the reference current errors was also presented in [26], showing a fast detection time, equivalent to 5% of the motor phase current fundamental period. However, this approach is not suitable for open-phase fault diagnosis, and an additional fault diagnosis indicator based on motor current variation analysis is presented.

The localization of the faulty switch can also be performed by the analysis of the current space vector trajectory diameter [27]. Nevertheless, this technique has serious drawbacks related to slow detection, tuning, and problems under low current values. Slidable triangularisation for a multi-switch open circuit fault diagnosis of microgrid inverters has been discussed in [28]. A fault diagnosis algorithm for microgrid three-phase inverter based on trend relationship of adjacent fold lines is proposed in [29]. A normalized method for DC and fundamental components of simplified Fourier series are proposed to locate multiple transistor open-circuit faults in three-phase induction motor drive as discussed in [30].

More recently, some contributions have been focused on the use of data-driven approach analysis to ensure effective open-circuit fault diagnosis in two levels [31–33] and multi-level [34] VSIs. In [31], line-to-line inverter voltages are used to extract fast Fourier transformation (FFT) based signatures, to achieve open-switch fault diagnosis in three-phase PMSM drives. However, this approach needs the use of supplementary voltage sensors which increases its cost. In [32], the authors present an online fault diagnosis method, based on the data-driven technology, to simultaneously identify multiple IGBT faults and current sensor faults in a three-phase inverter-fed induction motor. The open-circuit faults diagnosis and location of NPC inverters based on knowledge-driven and data-driven approaches is addressed in [34]. A similar approach is presented in [35]. In [36], a mixed approach using a sliding mode PI observer and a data processing algorithm is proposed to deal with open-circuit fault diagnosis in a grid connected PV NPC inverter.

Finally, intelligent artificial techniques such as neural networks or fuzzy logic have been successfully proposed as an open-circuit VSIs fault classifier [37–41]. In [40, 41], the normalized average currents are combined with fuzzy logic approach to obtain the faulty information of power switches. The proposed fault diagnosis approach can detect and locate both permanent and intermittent faults in power switches.

The state-of-the-art review shows that power switch fault diagnosis in voltage sources converters (VSCs) is an interesting research topic with various newly proposed algorithms and approaches. Recently, the use of predictive current errors was proposed to detect and identify power switch faults in electric variable speed drives [42–44]. In [42, 43], the use of a cost function is proposed to diagnosis only open-phase faults in PMSM drives. However, single and multiple open-circuit faults diagnosis are not discussed. Shi et al. [44], present a predictive current error associated to a moving integration filter-based algorithm for open-circuit faults diagnosis purpose in a three-phase induction motor. Multiple open-circuit fault diagnosis as well as robustness of the proposed method against the operating point variation was discussed. Nevertheless, the flowchart of the proposed approach is complicated. It has been shown that artificial intelligence and data-driven based techniques are more and more attractive for the monitoring of VSCs since they increase the reliability of the diagnosis approach. Indeed, artificial intelligence tools such as fuzzy logical reasoning have the ability of handling not only permanent open-circuit faults.
but also intermittent faults. This particular type of faults, in a power-semiconductor device, is due to electromagnetic interference or material aging. In practice, such fault corresponds to an intermittent loss of firing pulses of the switching power device. This mode of failure can be considered as an intermediate level between healthy and permanent faulty conditions.

Consequently, a new, simple, and robust open-circuit fault diagnosis algorithm is proposed in this work. The predictive currents in the (d,q) reference frame, estimated on the basis of the PMSM model under healthy operating mode, are compared to the reference (d,q) currents generated by the closed-loop control. The errors between these quantities are then used to generate appropriate diagnostic variables.

Finally, these diagnostic variables are combined into fuzzy symptoms to obtain the reliable information about the faulty switches. The proposed open-circuit fault diagnosis method may be considered as a mixed one, where its main advantages are:

1. No need of additional sensors, and therefore there is no increase of the systems’ costs.
2. Ability to diagnose single, multiple, and open-phase faults. Additionally, the diagnosis signatures associated to fuzzy rules lead to an effective diagnosis of permanent faults, as well as intermittent faults, which may improve the reliability of the system.
3. Robustness against parameters and operating point variations of the PMSM drive system, and easy implementation within a small computation time.

This paper is organized as follows. At first, in Section 2, the proposed diagnosis method is detailed. The fuzzy logic algorithm (FLA) and its rules are presented in Section 3. Section 4 presents the experimental setup and results for further validation. At last, the conclusions are summarized in Section 5.

2 | PROPOSED FAULT DIAGNOSTICS METHOD USING PREDICTIVE CURRENT ERRORS

2.1 | Diagnostic variables

The main idea of the proposed fault diagnostics method is to use the errors between the predicted Park’s current components and the reference currents, \(i_d^*\) and \(i_q^*\), generated by the closed-loop control, as fault indicators. The predicted errors are expressed as:

\[\begin{align*}
\Delta i_d &= i_d^*[k] - i_d[k+1] \\
\Delta i_q &= i_q^*[k] - i_q[k+1]
\end{align*}\]

where \(i_d[k+1]\) and \(i_q[k+1]\) denote the predicted dq stator current components at the \([k+1]\)th sampling time and \(i_d^*[k]\) and \(i_q^*[k]\) are the dq stator reference current components at the 4th sampling time.

Using the Euler approximation for a sampling time \(T_s: \frac{di}{dt} \approx \frac{i[k+1] - i[k]}{T_s}\), allows to express the dq rotating reference frame predicted stator currents of the PMSM, fed by the two level three-phase inverter shown in Figure 1 as:

\[\begin{align*}
\begin{cases}
\Delta i_d &= i_d^*[k] - i_d[k+1] \\
\Delta i_q &= i_q^*[k] - i_q[k+1]
\end{cases}
\]

\[\begin{align*}
\Delta i_d &= i_d^*[k] - i_d[k+1] \\
\Delta i_q &= i_q^*[k] - i_q[k+1]
\end{align*}\]

Assuming, for the actual sampling time, that: \(i_d[k] \approx i_d^*[k]\) and \(i_q[k] \approx i_q^*[k]\), Equation (3) can be simplified as:

\[\begin{align*}
\Delta i_d &\approx R/LT_i i_d[k] + T_i \omega i_q[k] - T_s/Lx_d[k] \\
\Delta i_q &\approx T_i \omega i_d[k] + R/LT_i i_q[k] - T_s/Lx_q[k] + \psi_s/\omega\]

Utilizing the inverse Park’s transformation, the three phase predicted current errors \(\Delta i_{abc}\) (where: \(x = a,b,c\)), are obtained as presented in Figure 2.

From Equation (4) and Figure 2, the waveform of the predicted current errors has a sinusoidal shape which may be represented by the following equation:

\[\Delta i_{abc} = \left\{\Delta I_1 \sin(\theta + \xi); \ \Delta I_1 \sin(\theta + \xi - 2\pi/3); \ \Delta I_1 \sin(\theta + \xi + 2\pi/3)\right\}^T\]

FIGURE 1  Diagram of a typical 2L-VSI feeding a PMSM

\[\begin{align*}
\Delta i_d &\approx R/LT_i i_d[k] + T_i \omega i_q[k] - T_s/Lx_d[k] \\
\Delta i_q &\approx T_i \omega i_d[k] + R/LT_i i_q[k] - T_s/Lx_q[k] + \psi_s/\omega\]

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Where $\Delta I$ is the predicted errors amplitude, $\theta$ is the fundamental phase and $\xi$ is a constant phase delay between the reference and the predicted currents.

In order to overcome the problems associated to the drive rated power and machine mechanical operating condition dependence, such as the speed and load levels, the predicted currents are normalized by dividing them by the modulus of the current Park’s vector that are given by:

$$
\Delta i_N = \frac{\Delta i_k}{\|\Delta i_0\|} = \frac{\Delta i_k}{\sqrt{\Delta i_d^2 + \Delta i_q^2}}
$$

where $x = \{a, b, c\}$

Hence, diagnostic variables resulting from the average values of the normalized errors may be defined as:

$$
\chi_x = \left< \Delta i_N \right> = \left< \frac{\Delta i_k}{\|\Delta i_0\|} \right> = \frac{1}{n} \sum_{j=1}^{n-1} \frac{\Delta i_k}{\|\Delta i_0\|}
$$

(6)

Under healthy operating conditions, the predicted currents follow their corresponding reference signals $i_{abc}^*$. Therefore, the predicted errors $\Delta i_{abc}$ will be close to zero and as a result, the diagnostic variables $\chi_x$ will be zero. However, if an IGBT fault occurs, the deviation between the predicted currents and their corresponding references will take the form of a positive or negative half cycle sinewave according to the affected IGBT.

Taking as an example an open-circuit fault occurred in IGBT $T_1$, as shown in Figure 1, during its positive half-cycle, the predicted current $i_{d+k}$ will be zero but its reference current $i_d^*$ is always a sinusoidal waveform. Therefore, during one fundamental period, the normalized predicted current error $\Delta i_N$ can be given by:

$$
\Delta i_N = \begin{cases} 
\sin(\theta + \xi) & 0 < \theta \leq \pi \\
0 & \pi < \theta \leq 2\pi 
\end{cases}
$$

(8)

Then, the phase $a$ diagnostic variable can be calculated as:

$$
\chi_a = \left< \Delta i_N \right> = \frac{1}{n} \sum_{j=1}^{n-1} \sin(\omega_j T_1) = \frac{1}{\pi} \approx 0.318 
$$

(9)

Consequently, the diagnostic variable associated with the faulty phase will be no longer null, and will converge quickly to its final value, crossing a defined threshold $h$ and leading to the detection of the corresponding faulty switch.

In the case of a double fault in the same inverter leg, the diagnostic variable defined by Equation (7) is unable to locate the fault because its corresponding value is close to zero. In this case, an additional diagnostic variable must be added in order to be able to detect and localize this type of fault. This variable can be defined as follows:

$$
\eta_x = 2 \left< |\Delta i_N| \right> - \left< (|\Delta i_{jN}|) + \left< |\Delta i_{zN}| \right> \right>
$$

(10)

Where: \{\{x, y, z\} = \{a, b, c\} and \{x, y, z\} = \{x, y, z\}

$\langle |\Delta i_{jN}| \rangle$ is the average absolute value of the predicted current error that, in healthy condition, is equal to:

$$
\left< |\Delta i_{jN}| \right> = \frac{1}{n} \sum_{j=1}^{n-1} \left| \Delta i_{jN} \right| = \frac{1}{n} \sum_{j=1}^{n-1} |\sin(\omega_j T_1)| = \frac{2}{\pi} \approx 0.64
$$

(11)

Therefore, for a double fault in phase $x$, the variable $\eta_x$ will not be zero because $\langle |\Delta i_{jN}| \rangle \neq \langle |\Delta i_{yN}| \rangle \neq \langle |\Delta i_{zN}| \rangle$ and will increase its value, allowing for an accurate indication of the occurrence of a fault in this phase.

To accomplish multiple fault diagnosis, and by using two threshold values $h$ and $l$, fault symptom variables can be formulated according to the following expressions:

$$
A_x = \begin{cases} 
N & \chi_x \leq -h \\
Z & -h < \chi_x < h \\
P & h \leq \chi_x 
\end{cases}
$$

(12)

$$
B_x = \begin{cases} 
\xi & \eta_x < h \\
P & h \leq \eta_x 
\end{cases}
$$

(13)

Where $N$, $Z$, and $P$ are the values of the desired domains: $N$ indicates a negative value, $Z$ indicates a zero value, and $P$ indicates a positive value.

The threshold values $h$ and $l$ can be empirically established by simply analysing the variable behaviour for different faulty operating conditions and by taking into account a tradeoff between fast detection and robustness against false alarms.

The short misfiring control signal in the inverter represents an abnormal operating condition. Therefore, on-line fault-detection methods must also take into consideration this type of faults. Consequently, the diagnostic variables should be able to diagnose and discriminate permanent as well as intermittent faults.

To deal with intermittent faults (Figure 3), these detection variables should be analysed using a FLA, which can still be used to find a solution by adding a third threshold $l$ to Equation (12) that can help to discriminate between intermittent and
permanently faults. Then, Equation (12) can be rewritten as:

\[
A_x = \begin{cases} 
N & X_x \leq -h_i \\
I_N & -h_i < X_x \leq -h_t \\
I_p & h_t < X_x \leq h_h \\
P & X_x \geq h_h
\end{cases}
\]  

(14)

Where \( I_N \) and \( I_p \) are the values of the intermittent domains, \( I_N \) indicates a negative intermittent value, and \( I_p \) indicates a positive intermittent value. Furthermore, the threshold values should be designed according to the values of \( X \) to guarantee the discrimination between different open-circuit faults.

2.2 PMSM Parameters sensitivity analysis

According to Equation (4), the predictive current errors \( \Delta i_d \) and \( \Delta i_q \) are a function of the PMSM parameters stator resistance \( R \), inductance \( L \), and permanent magnetic flux linkage \( \psi \), respectively. Consequently, it is important to study the effect of the variation of these parameters on the diagnostic variable \( X \).

When the parameter variation exists, the current prediction model (2) can be expressed as:

\[
\begin{align*}
\Delta i_d[k] &= (1 - \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s) i_d[k] + \omega T_s i_q[k] \\
\Delta i_q[k] &= (1 - \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s) i_q[k] - \omega T_s i_d[k] \\
\end{align*}
\]  

(15)

Where \( \Delta R \), \( \Delta L \) and \( \Delta \psi \) represent the parameter variation between the nominal and the actual values. Then, the prediction error between the reference currents \( i_{d0}^* \) and \( i_{q0}^* \) and model (15) subjected to parameter variation that defined the fault indicators can be obtained as:

\[
\begin{align*}
\Delta i_{d,\Delta R,\Delta L} &= i_{d0}^* - i_d[k+1]_{\Delta R,\Delta L} \\
&= i_{d0}^* - \left( 1 - \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s \right) i_d[k] + \omega T_s i_q[k] \\
\Delta i_{q,\Delta R,\Delta L} &= i_{q0}^* - i_q[k+1]_{\Delta R,\Delta L} \\
&= i_{q0}^* - \left( 1 - \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s \right) i_q[k] - \omega T_s i_d[k] \\
\end{align*}
\]  

(16)

As assumed that \( i_{d0}^* \approx i_{d0}^* k \) in the actual sampling time, Equation (16) can simplified as:

\[
\begin{align*}
\Delta i_{d,\Delta R,\Delta L} &\approx \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s i_d[k] - \omega T_s i_q[k] - \frac{T_s}{L + \Delta L} v_y[k] \\
\Delta i_{q,\Delta R,\Delta L} &\approx \omega T_s i_d[k] + \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s i_q[k] - \frac{T_s}{L + \Delta L} v_y[k] + \frac{\psi + \Delta \psi}{L + \Delta L} \omega T_s \\
\end{align*}
\]  

(17)

Therefore, the prediction error between the error-free model (4) and model (17) subjected to parameter variation can be obtained as:

\[
\begin{align*}
\Delta e_d &= \Delta i_{d,\Delta R,\Delta L} - \Delta i_d \\
&= \left( \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s i_d[k] - \omega T_s i_q[k] - \frac{T_s}{L + \Delta L} v_y[k] \right) \\
&\quad - \left( \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s i_q[k] - \omega T_s i_d[k] - \frac{T_s}{L + \Delta L} v_y[k] + \frac{\psi + \Delta \psi}{L + \Delta L} \omega T_s \right) \\
\Delta e_q &= \Delta i_{q,\Delta R,\Delta L} - \Delta i_q \\
&= \left( \omega T_s i_d[k] + \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s i_q[k] - \frac{T_s}{L + \Delta L} v_y[k] \right) \\
&\quad - \left( \omega T_s i_q[k] + \left( \frac{R + \Delta R}{L + \Delta L} \right) T_s i_d[k] - \frac{T_s}{L + \Delta L} v_y[k] + \frac{\psi + \Delta \psi}{L + \Delta L} \omega T_s \right) \\
\end{align*}
\]  

(18)

A simple mathematical development allows writing:

\[
\begin{align*}
\Delta e_d &= \frac{L \Delta R - L \Delta L}{L(L + \Delta L)} T_s i_d[k] - \Delta i_d \\
\Delta e_q &= \frac{L \Delta R - L \Delta L}{L(L + \Delta L)} T_s i_q[k] - \Delta i_q \\
\end{align*}
\]  

(19)
Model (19) implies that the variation or uncertainty of any PMSM parameter will lead to an error in the current prediction and therefore to an error in the diagnostic variables $\chi$ and $\eta$. The performance of proposed approach under PMSM parameters variations are illustrated in the following.

Figures 4(a–c) present simulation results of the steady state performance of the diagnostic variable $\chi$ under $\pm 50\%$ variation of nominal values of $R$, $L$ and $\psi_r$, respectively, considering various load and speed operating conditions. The nominal values of $R$, $L$ and $\psi_r$ are presented in Table 1. Regarding the sensitivity to the stator resistance variation, the results indicate a small variation of the diagnostic variable $\chi$ between 0.058 and 0.0675. Similarly, the diagnostic variable $\chi$ presents a slight variation between 0.053 and 0.071 regarding the permanent magnet flux linkage variation. However, the diagnostic variable $\chi$ presents a large variation value between 0.017 and 0.078 under stator inductance variation.

From these results, it is important to emphasize that the stator resistance and PM flux linkage variations have a low effect over the diagnostic variables, and their errors can be neglected, indeed [45–47]. Hence, the variation of the stator inductance $L$ has a more important impact, than the uncertainty on the stator resistance $R$ and PM flux linkage $\psi_r$ on the fault diagnostic variable $\chi$. At the same time, the analysis of the impact of the PMSM parameter variation on the fault diagnostic variable $\chi$ contributes to a better selection of the fault diagnostic thresholds.

### Table 1 PMSM parameters

| Parameter   | Value          |
|-------------|----------------|
| Power       | $P$ 2.2 kW     |
| Speed       | $N$ 1750 rpm   |
| Current     | $I$ 5.3 A      |
| Torque      | $T_L$ 12 Nm    |
| Flux linkage| $\psi_r$ 0.244 Wb |
| Resistance  | $R$ 1.72 $\Omega$ |
| Inductance  | $L$ 20.5 mH    |

3 \  | FUZZY LOGIC FAULT METHOD DESIGN

The fuzzy bases of the proposed method are extracted from the analysis of open-circuit faulty conditions as presented in Equations (13) and (14) where the fault symptom variables $A_x$ and $B_x$ should be fuzzed following these steps.

3.1 \  | Fuzzy logic problem formulation

The diagnosis procedure is based on the analytical and heuristic knowledge symptoms of the inverter. Heuristic knowledge in the form of qualitative process models can be expressed as if-then rules. In this paper, the analytical and heuristic symptoms are the fault symptom variables $A_x$ and $B_x$, which are the input of the fuzzy-based fault diagnosis algorithm. Based on the principle of fuzzy control theory and Equations (13) and (14), the six fault symptom variables $A_x$ and $B_x$ should be fuzzified as follows:

$$\begin{cases} A_x \in \{N, I_N, Z, I_P, P\} \\ B_x \in \{Z, P\} \end{cases}$$

Figure 5 shows the membership functions describing the input variables of the FLA. There are six membership functions according to the above analysis.
Similarly, the FLA output should be also fuzzified and the membership functions are illustrated in Figure 6. After fuzzification, the values 0, ±0.5, ±1, and 2 indicate the normal operation, intermittent, permanent open-circuit faults of the bottom and/or upper power switches, and finally double open-circuit fault of power switches in the same leg of the inverter. Therefore, the six FLA outputs provide not only the open-circuit fault information of a single power switch but also the entire leg fault information.

3.2 Fuzzy logic rules

Based on the relationships in Table 2, the fuzzy rules can be extracted. In general, the fuzzy control system consists of fuzzification, fuzzy inference, and defuzzification [41].

3.2.1 Fuzzification

This first step defines the mapping from normalized input to fuzzy variables by using the membership functions.

3.2.2 Fuzzy inference

The second step is fuzzy if-then rules, expressing fuzzy implication relation between the input fuzzy variables and the output fuzzy variables. In the proposed method, a Sugeno type fuzzy inference system is applied.

3.2.3 Defuzzification

This third step is the procedure that converts the fuzzy output set back into the crisp values and is called defuzzification. The method used in this paper is the min-max and weighted average “wtsum” method.

By using these rules, the generated fault signatures allow the detection and localization of the maximum number of faulty modes that can be distinguished, based just on the predicted current error analysis.

The block diagram of the proposed fault diagnostics strategy based on fuzzy logic algorithm and predictive current errors is illustrated in Figure 7.

4 EXPERIMENTAL RESULTS

The experimental setup depicted in Figure 8 comprises basically a 2.2 kW PMSM coupled to an AC machine used as load, a
diode bridge rectifier, a Powerex POW-RPAK three-phase VSI and a dSPACE DS1103 digital controller. Current sensors LEM LA 55-P are utilized, and an incremental encoder Hengstler RI 76TD is used as a position sensor. All results are obtained using the motor parameters listed in Table 1.

With the development of fast and powerful computational platforms, and to overcome the downsides of the traditional controller schemes (FOC, DTC, HCC), the use of model predictive control (MPC) in power electronics (including drives’ control) becomes more and more adopted in order to satisfy the demand for fast response and high performance in industrial applications [48–50]. The main concept is based on the calculation of the system’s future behaviour to obtain optimal values for the actuating variables. With this intuitive concept, predictive control can be applied to a variety of systems, in which nonlinearities constraints can be easily included, the multivariable case can be considered and the resulting controller is easy to implement.

MPC principles take into account the switching states of the inverter instead of using modulator. A discrete time model of the system is required to predict the future behaviour of the system for all the possible switching vectors. The control objectives of the MPC techniques are indicated in the cost function formula, which gives the conditions for selecting the best switching action to apply to reach the desired operating point. One of its advantages is the possibility to control different types of variables, such as currents, torque, flux, active and reactive power etc. As the current control is one of the most studied problems in power electronics, a model predictive current control MPCC in a rotating reference frame $(d,q)$ is adopted as a control for the PMSM drive, as illustrated in Figure 8.

The experimental implementation of the predictive control scheme requires a large number of calculations introducing a considerable time delay in the process. This delay can deteriorate the performance of the system. A cost function that assumes a minimum value for the predicted state, which takes into consideration the time delay compensation [51], is given by:

$$
J = [i_d^*(k) - i_d(k+2)]^2 + [i_q^*(k) - i_q(k+2)]^2 + J_{lim}[i_d(k+2), i_q(k+2)].
$$

$$
J_{lim}[i_d(k+2), i_q(k+2)] = \begin{cases} 
\infty & \text{if } |i_d(k+2)| > i_{d_{max}} \text{ or } |i_q(k+2)| > i_{q_{max}} \\
0 & \text{if } |i_d(k+2)| \leq i_{d_{max}} \text{ or } |i_q(k+2)| \leq i_{q_{max}} 
\end{cases}
$$

The last term of the cost function is a nonlinear function for limiting the amplitude of the stator currents, which is defined in Equation (22), where $i_{d_{max}},i_{q_{max}}$ is the value of the maximum allowed stator current magnitude. Finally, the voltage vector that minimizes the current error is selected and will be applied to the three legs of the inverter to run the machine in optimal conditions.
The control together with the diagnostic algorithm are implemented under Matlab/Simulink environment into the dSPACE DS1103 digital controller board using a sampling time $T_s = 35\mu s$. The PI parameters values, used to control the PMSM speed, $k_p$ and $k_i$ were set to be equal 0.04 and 1.5 respectively. Inverter power switch open-circuit faults are controlled using dSPACE ControlDesk software. These are accomplished by removing the gate command signals of the required IGBTs. It is important to emphasize that the “processor-in-the-loop” is an alternative solution for the digital implementation, where the controller interacts with the mathematical models of a real system that are implemented in Matlab/Simulink environment \[46, 52\]. However, the models should be able to exactly replicate the real operating conditions.

### 4.1 Robustness to load torque and PMSM parameter variations

The robustness of the proposed approach under healthy operating conditions of the PMSM drive is considered first. The three-phase stator currents and the diagnostic variables ($\chi_{abc}$ and $\eta_{abc}$) waveforms for a PMSM speed of 600 rpm, with a load torque variation, are presented in Figures 9(a.1–a.3). A sinusoidal waveform load torque variation from 0 to 6 (from 0% to 50% of the rated torque) is introduced. The behaviour of the diagnostic variables following this perturbation showed that their oscillations are still very small and slightly around zero.

Figures 9(b.1–b.3) present a second experimental result developed to show the steady-state behaviours of the diagnostic variables when the motor reference speed is 1200 rpm with a load variation from 2 to 6 Nm (from 17% to 50% of the rated torque). Here, as in the previous test, the time domain waveforms of two diagnostic variables show that they present small variations around the zero value.

The sensitivity of the proposed fault diagnostics approach to PMSM parameter variations is illustrated secondly. Two tests were carried out: the PMSM inductance was changed, first, to 50% of the measured value, and to 150% afterwards, under 50% of rated torque and a speed of 1200 rpm.

As it can be seen from Figure 10, slight variations of both diagnostic variables occurred, with parameter variations in a ±50% range. However, such variations are still low.

### 4.2 Threshold values selection

The selection of the correct fault detection thresholds is very important since it has a strong impact on the method’s robustness and immunity under healthy operation, as well as on the detection time associated with the diagnostic variables. Like in the existing diagnostic methods, the threshold value can be determined by analysing the behaviour of the corresponding diagnostic variables for the normal and faulty operations, and a trade-off between fast diagnosis and robustness to false alarms is normally taken into account. Indeed, a small threshold value may generate a false alarm under an inverter healthy mode, reducing the diagnosis robustness. On the contrary, a large threshold value would increase the diagnosis robustness, but also the diagnosis time. The diagnosis reliability and speed need to be balanced carefully.

In this work, there are three threshold values $t_i$, $t_h$ and $t_l$. These values are selected by considering several factors that affect the evolution of the diagnostic variables $\chi$ and $\eta$. These
factors regroup the transient states induced by the load torque and the motor speed change, the motor parameter variation, and the different levels that can be taken by the variables $\chi$ and $\eta$ in pre-fault and post-fault operation modes. Since the proposed diagnostic method is based on normalized variables, as presented in Equation (6), naturally the algorithm is independent of the fast-transient states induced by load and speed changes, which can guarantee an effective diagnostics and avoiding false alarms. On the other hand, as presented in Equation (2), the current prediction model considers the existence of the three machine parameters ($R$, $L$, and permanent magnetic flux linkage $\psi_p$). This means that the predictive current errors shown in Equation (17) are parameter sensitive, and the accuracy of the prediction model will directly influence the performance of the whole diagnostics method. Figure 4(a–c) show that a variation of one of the motor parameters makes it possible to increase the value of the diagnostic variable $\chi$ up to 0.08. Then, the impact of the motor parameter variations on the fault diagnostic variables helps on the choice of the threshold values.

Finally, the selection of the threshold values takes into account the behaviour of the diagnostic variables under healthy and faulty operation mode. As discussed in Section 2, it has been proven that $\chi$ is near 0 in healthy operation mode, but this variable increases quickly to its final value (equal 0.318) in the case of upper switches open-circuit faults or decreases to $-0.318$ in the case of lower switches open-circuit faults, as demonstrated in Equation (9). In practice, due to the erroneous measurements, modelling uncertainties etc., the diagnostic variables are not exactly equal to zero. Hence, to set the threshold $\delta$, various test cases under different healthy and faulty conditions and considering different rotational and loading levels are analysed, which is the same approach followed by most of the existing open switch fault diagnostic methods. By analysing the various test cases (Figures 4, 9, 10, and 14), it is observed that the peak value of the decision signal for a healthy phase reaches about 0.09. Moreover, analysing the various test cases with different combinations of open switch faults (Figures 11 and 12) under different operating conditions, it is observed that the decision signals of the faulty phases are always near 0.31. Generally, a small threshold value provides a faster diagnosis but also increases the risk of misdiagnosis. Thus, a compromise between the detection speed and robustness against false flags should be made. In this work, the threshold values $t_h$ and $t_l$ are conservatively set to 0.25 to provide a good margin for avoiding the misdiagnosis in critical operating regimes.

In the same way, as the intermittent fault is an abnormal operating condition for the VSI, the threshold value related to this fault type can be chosen taking into consideration all the factors mentioned above. As a result, the value of 0.1 for the threshold $t_i$ guarantees a good localization performance.

With a similar reasoning, the threshold $t_i$ is selected by considering the behaviour of the diagnostic variable $\eta$ in pre-fault and post-fault operation modes. This variable is around zero when the VSI operates free from faults, and is equal to 0.318 when an open-switch fault occurs in the VSI. However, as demonstrated analytically in Equation (11), this variable increases immediately to the value $+0.64$ when a double open-switch fault in the same leg occurs. Therefore, the threshold $\eta$ is fixed to 0.5, permitting a large dissymmetry between the pre-fault and post-fault operation modes. Here, it should be noticed that an optimization algorithm, with speed detection and method robustness as constraints, can be formulated to derive the threshold values.

Finally, the $t_i$, $t_h$, and $t_l$ values are also verified by various experimental tests in the laboratory under several operating conditions. It is expected that the chosen threshold values allow a fast fault detection and identification with a high immunity of the proposed diagnostic method to false alarms.

### 4.3 Open circuit fault diagnosis

Figure 11 shows the time domain waveforms of the three phase currents for a double fault in the power switch $T_1$ firstly, and in
T1 secondly, under 50% of the rated load torque, and a speed of 1200 rpm.

When an open-circuit fault in IGBT T1 is applied at the instant \( t = 0.6 \) s, the positive half-cycle of the current \( i_a \) is eliminated. Consequently, the diagnostic variable \( \chi_a \) increases immediately to converge approximately to near 0.25, exceeding the threshold \( \eta \), which is set equal to 0.25. The remaining variables \( \chi_b \) and \( \chi_c \) converge approximately to \(-0.15\). As a result, the identification flag IGBT12 increases immediately to 1 after 2.6 ms of the fault occurrence, corresponding to 26% of the motor currents fundamental period.

The open-switch fault in IGBT T4 is added to the fault in T1 at a time \( t = 0.8 \) s. When the second fault is introduced, the diagnostic variable \( \chi_a \) decreases immediately to the value of \(-0.32\) and under the threshold \(-\eta\). The third diagnostic variable \( \chi_c \) increases to 0.01 when the second fault in T4 is added, allowing an effective detection and localization of both failures. The time detection of the second failure in IGBT T4, which is 1.2 ms after the fault occurrence at the instant \( t = 0.8012 \) s, which corresponds to 12% of the motor current fundamental period.

The performance of the proposed algorithm regarding the diagnosis of an open-phase fault is depicted in Figure 12. Firstly, a single open-circuit fault in IGBT T1 is introduced at a time \( t = 0.615 \) s, for a speed of 600 rpm and a load torque equal to 4 Nm. The faulty IGBT is detected when the fault diagnostics flag IGBT12 switches from 0 to 1 at a time \( t = 0.62 \) s, corresponding to an interval of 25% of motor currents fundamental period.

When the second fault, in IGBT T2, is added at a time \( t = 0.815 \) s, the behaviour of the fault diagnostic variables automatically changes. Regarding both diagnostic variables for this kind of situation (open-phase fault), it is clear that the second diagnostic variable \( \eta_c \) assumes an important role now. When the open-phase fault occurs, the diagnostic variables \( \chi_{abc} \) are zero whereas the diagnostic variable \( \eta_c \) increases immediately to approximately 0.65, and the remaining \( \eta_a \) and \( \eta_b \) decrease to around \(-0.3\), as presented in Figure 12(b, c) respectively. Hence, the open-phase fault is detected when the corresponding fault diagnosis flag Leg4 changes from 0 to 2, 15 ms after the fault occurrence, which corresponds to 75% of the motor currents fundamental period.

The steady state performance of the proposed fuzzy logic algorithm under various intermittent faults in the VSI power switches is addressed in this section. Firstly, an intermittent open-circuit fault in IGBT T1 is applied at a time \( t = 0.307 \) s, under a speed of 1000 rpm and a load torque equal to 3 Nm, as shown in Figure 13. The faulty IGBT is localized by the switching state of the flag IGBT12 that changes from 0 to 0.5 at \( t = 0.312 \) s, in an interval of 41% of the fundamental period.

When the permanent fault in IGBT T1 is applied at \( t = 0.607 \) s, the behaviour of the diagnostic signals automatically changes by increasing the flag IGBT12 of the affected power switch from 0.5 to 1 at \( t = 0.612 \) s with a time equal to 41% of motor currents fundamental period, indicating that it is a permanent fault in the power switch T1.

The performance of the proposed fault diagnostic approach during a speed transient is presented in Figure 14, which shows the experimental results of the PMSM stator currents with the diagnostic variables for a single power switch open-circuit fault in IGBT T1 when the motor accelerates from 600 to 1200 rpm under 25% of rated torque. Under healthy operating conditions, and during the speed variation, it can be seen that both diagnostic variables still oscillate around zero, and no false alarms are generated. At the instant \( t = 0.614 \) s, an open switch fault in T1 occurs. Therefore, the diagnostic variable \( \chi_a \) increases immediately to converge approximately to near 0.32, exceeding the threshold \( \eta \) and the other variables \( \chi_b \) and \( \chi_c \) decrease approximately to \(-0.18\). As a result, the identification flag IGBT12 changes its state from 0 to 1 after 6 ms of the fault occurrence, corresponding to 45% of the motor currents fundamental period.

These results illustrate the effectiveness of the proposed approach for detecting open-circuit faults in both steady-state and transient operating conditions of the drive.
4.4 Comparison between proposed method and other fault diagnosis methods

A comparison between the proposed approach and other fault diagnostics strategies presented in the literature, using reference current errors [26], or fuzzy logic [39–41] to detect the open circuit faults is presented in Table 3.

Compared to the approaches presented by Zidani et al. [39], Slezynski et al. [40] and Yan et al. [41], which use fuzzy logic as a tool for diagnostics purpose, the approach proposed here is able to perform the diagnosis and to classify intermittent, single, and multiple open-circuit faults in a detection time lower than the ones achieved by those algorithms.

Compared to the approach proposed by Estima et al. [26], this new approach presents a similar performance regarding robustness and time to diagnostics, but allows in addition the discrimination between intermittent and permanent faults type. Thanks to the availability of high-performance real time digital processors, the proposed algorithm has a low complexity in terms of computational resources demanding, and offers smart diagnostics prospects.

Finally, the obtained results show that the speed of the diagnostics approach is fast enough to allow the drive supervision system to take appropriate actions to protect the system and/or to ensure its continuous operation.

5 CONCLUSION

This paper presents a new fault diagnosis approach to handle with open circuit faults in three phase VSIs of PMSM drives.
The proposed algorithm uses the errors between the reference currents, generated by the main control, and the predicted currents. It utilizes the variables already used by the main control of the drive, thus avoiding the need for any extra sensors or electric devices, and therefore decreasing the complexity and cost of the proposed diagnostic scheme.

The obtained results show that, in addition to the high robustness of the fault diagnostics algorithm regarding high and fast load torque transients, an effective diagnosis is obtained for both intermittent and permanent single and multiple open-circuit faults. It can also discriminate intermittent faults from permanent ones.

Comparing to other strategies described in the literature, the proposed approach offers a fast time to diagnostics (12–75% of the motor currents fundamental period). The obtained performance offers very good prospects regarding the use of artificial intelligence techniques in the research field of fault diagnosis in power converters.

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