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Detection and Localization of Phase Insulation Fault in a Set Inverter-Induction Motor

Bilal Djamal Eddine Cherif, Sara Seninete, Hilal Rahali, and Mostefa Tabbakh

Abstract Stator current analysis for preventive maintenance is an essential tool for industries. Its use is intended to serve three levels of analysis: supervision, diagnosis and monitoring of the state of damage to equipment. The main objective of this paper is to propose a diagnosis and monitoring method based on the analysis of the stator current for the detection and localization of a short-circuit fault occurred on the inverter (insulation fault of a phase). The proposed method uses signal processing techniques (temporal and spectral domain) combined with a machine learning technique to locate the faulty phase. The study begins with the application of the fast Fourier transform (FFT) to detect the harmonic characterizing the short-circuit fault of a phase of the inverter, and then a statistical study based on the skewness calculation is performed at the stator current spectrum for each phase. The second part of the study applies the random forest RF to locate the faulty phase. The features used to train the RF model are the amplitude of the harmonic f_{150} and the value of the skewness. The results obtained by RF show a good performance with a very high classification rate equal to 98.98%.

Keywords Induction motor · Inverter · Fault · Insulation fault · FFT · Random forest

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1 Introduction

Significant development has been carried out on the diagnosis of variable speed electric drives in the presence of induction motor faults such as the broken of one or more consecutive bars and/or portion of a short-circuit ring, the running short-circuit between turns in the windings and the different types of eccentricities. Or in the presence of static converter faults, such as the open-circuit fault or short-circuit fault of an IGBT, insulation fault of a phase and short-circuit fault of a DC stage [1].

Static converters, particularly inverters, are predominantly present in variable speed electric drive systems. Data concerning reliability, from the literature justify the scope envisaged for the implementation of fault or fault tolerance. The percentage distributions of faults in an inverter are: 60% DC stage short-circuit; 31% IGBT fault; 6% diode fault [2, 3].

In recent decades, the early detection and diagnosis of faults affecting inverter-induction motor assemblies has been the subject of much research. There are several types of detection and diagnosis techniques, namely vibration analysis, acoustic analysis and thermography. However, these methods are mainly recommended for the detection of mechanical faults [4].

A new technique is also used more and more in recent years. It is based on the analysis of the stator current. Its peculiarity lies in the fact that the stator current contains information on almost all the faults that may appear at the level of the inverter-induction motor assembly. The analysis of stator currents in the frequency domain remains the most commonly used method, especially for stationary regimes, because the resulting spectrum contains a source of information on the majority of electrical faults [5, 6].

For the detection of fault, several researchers have identified and developed various signal processing techniques allowing the detection and diagnosis of insulation phase fault of the inverter. Typical techniques include spectral analysis (Fast Fourier transform FFT) [7].

The famous fast Fourier transform (FFT) algorithm for calculating FFT is based on the recursive use of these formulas. When N is not a power of two, analogous calculation using a prime factorization leads to the same order of magnitude $\mathcal{O}$ (N $\log_2$ N) of the number of multiplications and additions [8, 9].

For the automatic monitoring of complex devices, it is necessary to develop diagnostic systems that have a certain ability to adapt to new situations (learning), and allow reliable recognition of the operating mode in which the system evolved [10].

Random forest methods are based on the combination of elementary classifiers of decision tree types. Individually, these classifiers are not known to be particularly efficient, but they have interesting properties to exploit in an EOC: they are not known to be particularly unstable. The specificity of trees used in random forests is that their induction is disturbed by a random factor, in order to generate diversity as a whole. It is on the basis of these two elements using decision trees as elementary classifiers and involving randomness in their induction that formalism of random forests was introduced [11].

In the field of inverter diagnosis, most papers have been published for the detection and localization of open-circuit faults of an IGBT. We cite some paper. The authors in [12], suggested Park's vector method to detect and locate the open-circuit fault of an IGBT. This technic is based on the mean value of Park vector currents in the plan (*d*–*q*) and the determination of the phase angle. The authors in [13, 14], suggested the standardized method of direct current. This technic is based on direct components and the first component of the harmonic coefficients of alternative currents. To detect and localize the defective IGBT, the DC component is divided by the absolute value of the first harmonic and compared to a threshold (set at 0.45). This technic has a certain drawback when implemented in a closed loop control system. The same authors proposed second method the standardized direct current method. To increase process reliability and avoid false alarms, the standardized direct current process has been refined.

The rest of this paper is organized as follows: in Sect. 2, we will discuss the modeling of two-level voltage inverter. Section 3, introduces the control of the inverter based on PWM-Vector. In Sect. 4, we introduce the inverter phase short-circuit fault (phase insulation fault) and their impact of the fault on the behavior of the induction motor. Section 5 introduces the automatic surveillance technic: The first part is based on the FFT for fault detection and the second part is based on machine learning to locate the faulty phase. Finally, Sect. 6 closes this paper with a conclusion.

2 Inverter Modeling

Figure 1 shows a block diagram of a three-phase voltage inverter with two levels.

According to the simplified diagram of the three-phase inverter, there is a relationship between the phase-to-neutral voltages coming from the inverter in points A,

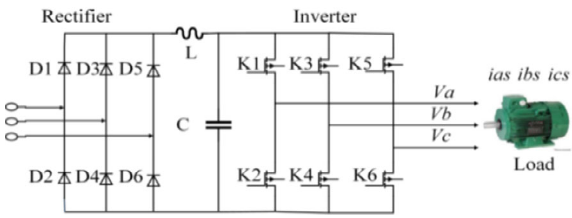


Fig. 1 Two-level three-phase voltage inverter

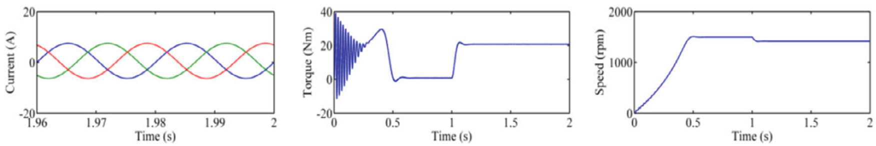


Fig. 2 Stator current, torque and speed in the case of healthy inverter

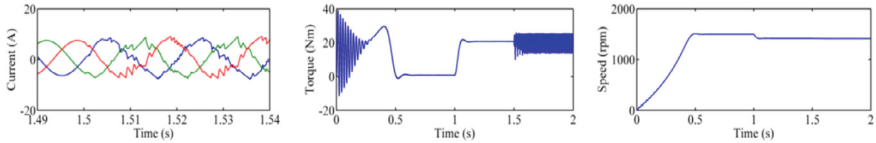
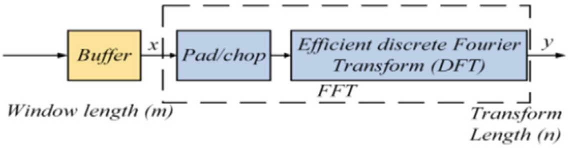


Fig. 3 Stator current, torque and speed in the case of inverter with one phase insulation fault

Fig. 4 Fast Fourier transform algorithm



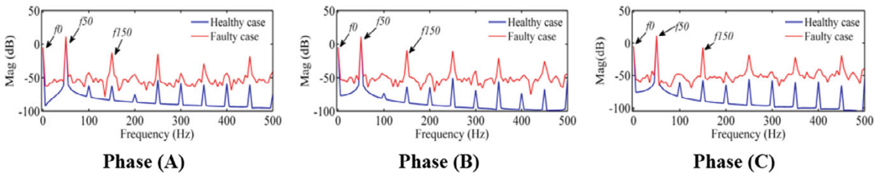
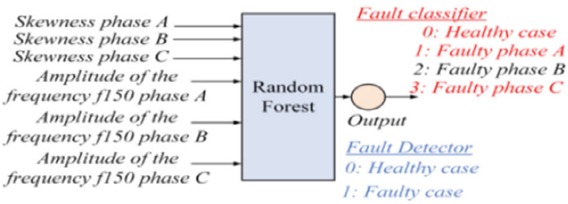


Fig. 5 Spectrum of the stator current of each phase for the healthy inverter and faulty inverter single phase insulation phase (A)

Fig. 6 Schematic diagram of a fault classifier based on random forest



B and C and their values with respect to the midpoint (0), defined by the following matrix relation [15]:

$$\begin{bmatrix} V_A \\ V_B \\ V_C \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix}\begin{bmatrix} V_{A0} \\ V_{B0} \\ V_{C0} \end{bmatrix} \quad (1)$$

The voltages V_A, V_B and V_C represent the voltages from the inverter to supply and control the induction motor. Knowing that [16]:

$$\begin{cases} V_{A0} = \dfrac{E}{2} S_a \\ V_{B0} = \dfrac{E}{2} S_b \\ V_{C0} = \dfrac{E}{2} S_C \end{cases} \tag{2}$$

The control signals Si (i = a, b and c) are given by:

$$\begin{aligned} S_i &= 1\, K_i \text{ is } \boldsymbol{ON} \text{ and } K_i' \text{ is } \boldsymbol{OFF} \\ S_i &= 0\, K_i \text{ is } \boldsymbol{OFF} \text{ and } K_i' \text{ is } \boldsymbol{ON} \end{aligned}$$

The voltages delivered by the inverter become:

$$\begin{bmatrix} V_{A0} \\ V_{B0} \\ V_{C0} \end{bmatrix} = \frac{E}{3} \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} S_a \\ S_b \\ S_c \end{bmatrix} \tag{3}$$

The determination of the phase-to-phase voltages between two phases amounts to applying the following relation [17]:

$$\begin{cases} V_{AB} = V_A - V_B \\ V_{BC} = V_B - V_C \\ V_{CA} = V_C - V_A \end{cases} \tag{4}$$

The relation between the vector $[S_a, S_b \text{ and } S_c]^T$ and the vector of line voltages $[V_{ab}, V_{bc} \text{ and } V_{ca}]^T$ is given by:

$$\begin{bmatrix} V_{AB} \\ V_{BC} \\ V_{CA} \end{bmatrix} = E \begin{bmatrix} 1 & -1 & 0 \\ 0 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} S_a \\ S_b \\ S_c \end{bmatrix} \tag{5}$$

2.1 Inverter Control

The strategy proposed in this article is vector PWM (pulse width modulation). This strategy consists of the six steps [18]:

Step 01: calculate the reference vector V_{ref}.

Step02: calculate phase θ and sector i.

Step 03: translate to the first sector.

Step 04: Determine the triangle.

Step 05: Determine the vectors and calculate the switching times.

Step 06: Return to the initial sector.

Figure 2 shows the simulation results of the inverter- induction motor assembly with the triangular-sinusoidal technique.

We simulated the model of induction motor associated with a voltage inverter controlled by the vector PWM technique as above with no load, then a resistive torque of 20 Nm was applied at the instant $t = 1$ s. If we compare these results with the model without an inverter, we see that they are similar but they exhibit oscillations around an average value, these oscillations are mainly due to the presence of harmonics in the voltages delivered by the inverter.

2.2 Inverter with One Phase Insulation Fault

In the event of accidental grounding of a phase of the inverter, this phase is connected to the neutral of the induction motor thus stablishing a short-circuit path through the inverter and the impedance of the differential mode filters and common mode. The disturbance of the induction motor control is not very important since the phase currents are regulated and a slight distortion is generated by the ripple of the direct voltage. On the other hand, large currents are taken from the network with a high distortion and a strong current circulates through the ground path [19].

By opening the contactors of the equipment, the fault is confined in the inverter-induction motor assembly and the loss of controllability of the inverter leads, in the absence of reconfiguration of the control, to a degraded regime with high currents and significant torque ripples. It is then possible to proceed with the blocking of the inverter to quickly suppress the current flow. If, however, the fault occurs in the over speed range, blocking the inverter no longer prevents the flow of current and the insulation envisaged is then beneficial to reduce the duration of the fault regime [19].

Figure 3 shows the simulation results of the induction motor supplied by a voltage inverter under a phase insulation fault.

The simulation results are presented in Fig. 3, the latter represent the curves: stator current, speed of rotation and electromagnetic torque. In the abnormal regime, these results in current amplitudes of the order of the rated current and a strong ripple torque. Only the motor sizing limits the short-circuit current, which however does not flow through the inverter. As this degraded speed is self-sustaining, it results in a loss of actuator controllability.

3 Detection and Location of a Phase Insulation Fault

3.1 Detection of a Phase Insulation Fault Based on FFT

When diagnosing phase insulation fault, FFT will be applied to estimate the fundamental frequency. And the other frequency components corresponding to the fault must be calculated. The phase insulation is one of the common faults in the inverter. The characteristic frequency component of the induction motor stator current with phase insulated in the inverter depends on the location of sideband frequency around the supply frequency (50 Hz). FFT response in the steady state region is used as a tool to detect the phase insulation fault. The normal operation of the motor should have peaked at FFT response located at 50 Hz without any sidebands, and if any fault happened, the sideband will appear.

Figure 4 shows the fast Fourier transform algorithm.

Using Matlab instruction, to implement FTT for vectors of length N as in following equations [20]:

$$y = fft(x) \tag{6}$$

where:

$$x(k) = \sum_{j=1}^{N} x(j)\omega_N^{(j-1)(k-1)} \tag{7}$$

$$x(j) = \left(\frac{1}{N}\right)\sum_{j=1}^{N} x(k)\omega_N^{-(j-1)(k-1)} \tag{8}$$

$$\omega_N = \mathrm{e}^{(-2\pi i)/N} \tag{9}$$

Figure 5 shows the spectrum of the stator current of each phase for the healthy case and the case of a single phase insulation fault phase (A).

A comparative study between the spectrum of the healthy case and the spectrum of the faulty case under phase insulation clearly shows a particular frequency signature around 150 Hz. It should be noted that the frequency $f_{150} = 3\,fs = 150$ Hz is the frequency which characterizes the phase insulation fault.

Table 1 summarizes the amplitudes of the harmonics (f_0, f_{50} and f_{150}).

- ***Skewness***

The skewness coefficient corresponds to a measure of the skewness of the distribution of a random variable [21]:

$$skewness = \frac{\sum_{i=1}^{N}[x(i) - \overline{x}]^3}{(N-1)\sigma^3} \tag{10}$$

Table 1 Amplitude of the Harmonics (f_0, f_{50} and f_{150})

Case	Phase (A)			Phase (B)			Phase (C)		
	f_0	f_{50}	f_{150}	f_0	f_{50}	f_{150}	f_0	f_{50}	f_{150}
Healthy case	– 4.7	10.7	– 61.9	– 4.7	10.7	– 63.4	– 4.7	10.7	– 57.5
Faulty phase (A)	– 4.7	11.06	– 12.9	– 4.7	10.31	– 9.02	– 4.7	11.3	– 7.13
Faulty phase (B)	– 4.8	11.17	– 9.4	– 4.7	11.33	– 13.02	– 4.7	10.3	– 18.8
Faulty phase (C)	– 4.7	10.19	– 11.8	– 4.7	11.05	– 10.1	– 4.7	11.3	– 13.5

Table 2 Skewness Values

Case	Phase (A)	Phase (B)	Phase (C)
Healthy case	0.00051234	0.000059511	0.00046402
Faulty phase (A)	0.0035	0.0020	– 0.0027
Faulty phase (B)	– 0.0169	0.0090	0.0010
Faulty phase (C)	0.0021	0.00020	0.0045

Table 2 summarizes the values of the skewness coefficient.

Once the Skewness value reaches its maximum, the correspondent phase contains then the fault.

3.2 Localization of a Phase Insulation Fault Based on Random Forest (RF)

This classification algorithm is given by the following steps.

Step 01: Select the random data points K from the training set.

Step 02: Build the decision trees associated with the selected data points (subset).

Step 03: Choose the N number for the decision trees that you want to create.

Step 04: Repeat steps 01 and 02.

Step 05: For new data points, search predictions of each decision tree and assign the new data points to the class that wins the majority votes.

Figure 6 shows the features used to form the random forest models and Fig. 7 shows the accuracy as a function of the trees number.

The accuracy achieves its maximum value when the Trees number equal to 39.

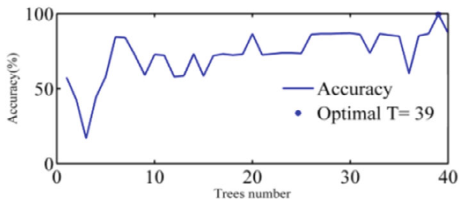


Fig. 7 Accuracy as function of the trees number

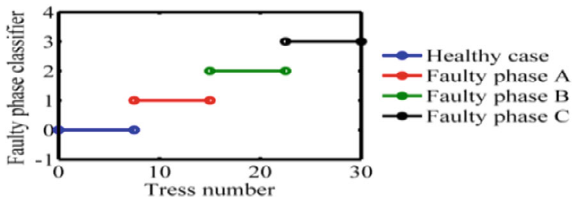


Fig. 8 Waveforms of output values from the machine learning technique based on random forest

Figure 8 shows the waveform of the output of the random forest-based defect classifier.

The values obtained indicate that the classifier model selected by random forest has had considerable success in detecting and classifying phase insulation faults. After several simulation tests, the classification results obtained clearly demonstrate and confirm the effectiveness of the proposed diagnostic method with high recognition accuracy of 98.979%.

3.3 Evaluation Criteria

The data classification performance is evaluated by the calculation of [22]:

- ***Accuracy***

The percentage of correctly classified examples is calculated according to:

$$Acc = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{11}$$

- ***Sensitivity***

Is the ability to get a positive result when the defect is present. It is calculated according to as:

$$Sens = \frac{T_P}{T_P + F_N} \tag{12}$$

Table 3 Evaluation criteria of random forest

Technique	Accuracy	Sensitivity	Specificity	Recall	g-mean
Randon Forest	0.9898	0.9795	0.9914	0.9798	0.9795

- ***Specificity***

Is the ability to get a negative result when the defect is not present. It is calculated according to as:

$$Spec = \frac{T_N}{T_N + F_P} \tag{13}$$

- ***Recall***

Is the ability to obtain a positive result when the defect is present. It is calculated according to as:

$$\mathrm{Re}c = \frac{T_P}{T_P + F_N} \tag{14}$$

- ***G-mean***

It is the geometric mean of sensitivity and precision given as:

$$GSP = \sqrt{sens \times prec} \tag{15}$$

Table 3 summarizes the Evaluation criteria of the random forest method.

4 Conclusion

The automatic monitoring of an inverter phase short-circuit fault (single phase insulation) is particularly illustrated in this paper. The stator current signals analyzed are provided from the simulation work. The proposed method consists of using a signal processing based on the fast Fourier transform, as well as a machine learning technic based on Random Forest. In this context the FFT is used to detect the frequency which characterizes the short-circuit fault of a phase of the inverter ($f_{150} = 150$Hz) and also to calculate the skewness coefficient to measure the asymmetry and the distribution of a random forest variable. These characteristics obviously enrich the random forest which offers a good classification revealing excellent performances by giving the fault phase. The proposed RF structure has the advantage of being simple in modeling and in implementation. The results obtained proved the efficiency of the method, giving an accuracy of 98.98%.

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