

Diagnosis of Induction Machines Using External Magnetic Field and Correlation Coefficient

Miftah Irhoumah

Univ. Artois, EA 4025 LSEE
F-62400, Béthune, France

Miftahaldwiab_irhoumah@ens.univ-
artois.fr

David Mercier

Univ. Artois, EA 3926 LGI2A
F-62400, Béthune, France

David.mercier@univ-artois.fr

Remus Pusca

Univ. Artois, EA 4025 LSEE
F-62400, Béthune, France

Remus.pusca@univ-artois.fr

Eric Lefèvre

Univ. Artois, EA 3926 LGI2A
F-62400, Béthune, France

Eric.lefevre@univ-artois.fr

Raphael Romary

Univ. Artois, EA 4025 LSEE
F-62400, Béthune, France

Raphael.romary@univ-artois.fr

Abstract— The statistical analysis of faulty induction machine has proved to be a useful tool for prediction of main effects due to faults. So this paper proposes a mathematical model for diagnosis of the inter-turn short circuit in the stator winding of electrical machines. This model uses the Pearson correlation coefficient and a pair of sensors, placed at 180° from each other around the machine to measure the external magnetic field in the machine vicinity. The data obtained from each sensor are analyzed and compared with each other when the load varies. It will be shown that one can obtain high probability to detect the fault using this method and experimental results show that the new method has high reliability level for fault detection. On the other hand, the presented method does not require any knowledge of a presumed machine healthy former state.

Keywords : induction machines, fault diagnosis, magnetic flux sensors, correlation coefficient, magnetic field, inter-turn short-circuit.

I. NOMENCLATURE

r	Pearson correlation coefficient
IM	Induction Machines
S1	Sensor 1
S2	Sensor 2
$As1$	Value of Sensor 1
$As2$	Value of Sensor 2
x	Samples of the first variable
y	Samples of the second variable
N^s	Stator per pole pair tooth numbers
N^r	Rotor per pole pair tooth numbers
f_r	Rotor frequency
F_s	Stator Frequency
L0	Load = 0 watt (no load)
L1	Load = 128 watt
L2	Load = 385 watt
L3	Load = 750 watt
L4	Load = 1240 watt
L5	Load = 1500 watt
P	Positions of short circuit
I _{cc}	Current of short circuit

II. INTRODUCTION

The machine failures in industry lead to losses in production time and cost of repairing. Among the usual faults in induction machines, mechanical faults represent 50-60%, stator faults represent 40-50% and rotor faults represent 10-20% of the total failures. Mechanical faults are associated in most cases to eccentricity. Therefore, detection and diagnosis of incipient faults in induction motors is desirable for product quality and to improve the operational efficiency [1]. In this context, many researches have been focused on the detection of incipient stator inter-turn short circuit fault in induction machines [2]. This failure is generally the consequence of combination of several conditions as aging, high temperatures, machine insulation degradation and large dv/dt in the winding terminals.

Over the last decade, different fault detection techniques have been developed and the technology in this field is still in permanent evolution [3]. Recently, studies concerning electrical machines, drives condition monitoring and fault diagnosis has presented new advances in the diagnosis methods for detection of incipient faults [4-6]. In order to improve the fault detection, diagnostic methods use techniques as Wavelet [7], Artificial Neural Networks [8], Fuzzy Logic [9], or Improved Artificial Ant Clustering Technique [10]. The experimental results prove the efficiency of these approaches. Although their efficiency has been demonstrated the generalization of these methods in industry is still limited because of their relatively high cost. Moreover, the implementation of such systems is expensive, requires more data acquisition equipment and additional measurements, and takes a relatively long time [11].

The aim of the paper is to develop a diagnosis method based on the external magnetic field analysis. The principle exposed in [4] is extended by introducing the calculation of the Pearson correlation coefficient between two signals delivered by two sensors S1 and S2 when the load varies. These sensors are located symmetrically relatively to the axis of the machine

(spatial shift of 180°) [12]. This method, based on the measurement of the magnetic field outside the machine, is interesting because it is non-invasive, inexpensive and easy to implement. It uses the load variation to perform the fault detection. Furthermore, this method does not require the knowledge of the machine healthy state [4].

This paper is organized as follows: next section presents the methodology of the diagnosis procedure, fourth section presents the basic concepts on Pearson correlation coefficient and last section presents the experimental results demonstrating the validity of the proposed method.

III. METHODOLOGY

A test bench, schematized in Fig.1, allows us to test the method in a three phase squirrel-cage induction motor, which has been rewound and whose elementary sections are extracted allowing us to create a short-circuit fault at different positions of the stator winding. Then, different measurements from each of the two sensors are obtained for different load conditions.

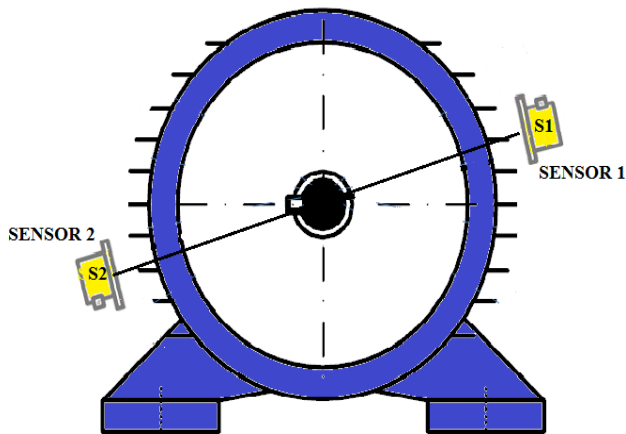


Fig. 1. Position 1 of sensors S1 and S2 placed at 180° around the induction machine.

In the proposed method, two sensors S1 and S2 are placed at 180° from each other around the induction machine. Those sensors measure the external magnetic field in the vicinity of the machine. The procedure uses the calculation of Pearson correlation coefficient r between specific harmonic obtained from the signals delivered by S1 and S2 in healthy and faulty conditions of the machine. These specific harmonic is sensitive to a stator inter-turn short circuit, and it is computed from an analytical model of the fault that consider the slotting effect [12]. Therefore, the corresponding frequency depends on the number of rotor slot N^r and the rotor rotating frequency f_r . For a 50Hz supply frequency this sensitive frequency is given by:

$$F_s = 50 + N^r * f_r. \quad (1)$$

Let consider As_1 and As_2 the amplitudes of these variables in the both positions, which are used as inputs to calculate the Pearson coefficient. Different Values of As_1 and As_2

corresponding to various load conditions are considered. Taking into account a load increase, the method can be described as follows:

- If the values of r is close to 1, there is a strong positive linear correlation between As_1 and As_2 , this means that variables vary similarly. This indicates no fault in the stator windings of the machine as shown in Fig. 2.

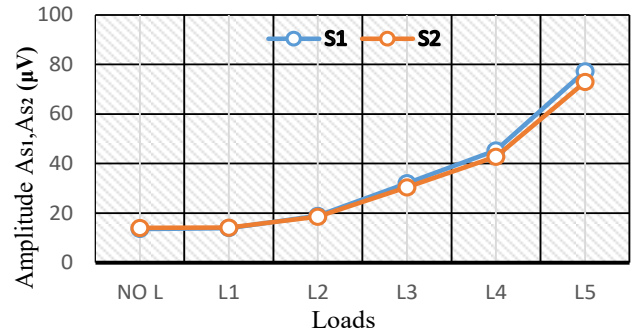


Fig.2. Relationship between signals As_1 and As_2 for healthy condition of the machine and load variation when r is close to 1.

- If the value of r is close to 0, there is no linear correlation or a weak linear correlation between As_1 and As_2 . This means that the variables do not change similarly and it indicates a fault in the stator windings of the machine as shown in Fig.3.

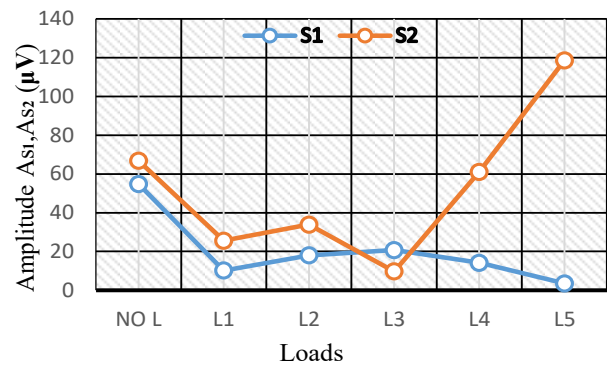


Fig.3. Relationship between signals As_1 and As_2 for faulty condition of the machine and load variation when r is close to 0.

- If the value of r is close to -1, there is a strong negative linear correlation between As_1 and As_2 and the variables vary in the opposite direction. This also indicates a fault in the stator windings of the machine as it is shown in Fig.4.

In faulty conditions, the correlation coefficient can vary and it depends on the load and on the short-circuit current in the stator windings. This study analyses the Pearson correlation coefficient to determine the status of the machine and compare the values of Pearson correlation coefficient when the two sensors S1 and S2 are placed and not placed at 180° from each other.

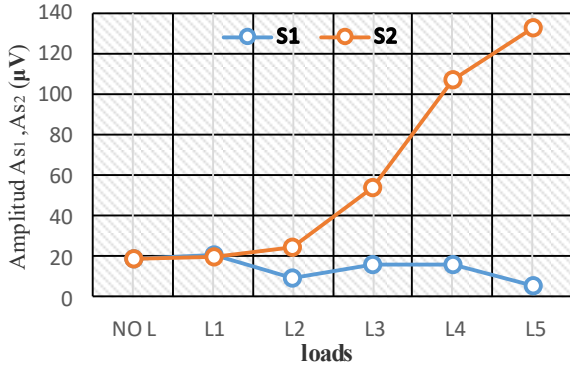


Fig.4. Relationship between signals As_1 and As_2 for faulty condition of machine and load variation when r is close to -1

IV. PERSON CORRELATION COEFFICIENT

A. Basic Concepts

Pearson correlation coefficient r is a mathematical development [6] used to show the strength between two variables x and y where the value of r ranges between (-1) and (+1) [13], [14]. Correlation measures the degree to which two variables move in relation to each other. Strong positive correlations mean that the two variables tend to increase together at the same time, while strong negative correlations show that they move apart at the same time. Generally, this coefficient is often symbolized in mathematical formulas by letter r . Fig.5 show the values of r ranges between (-1) and (+1).

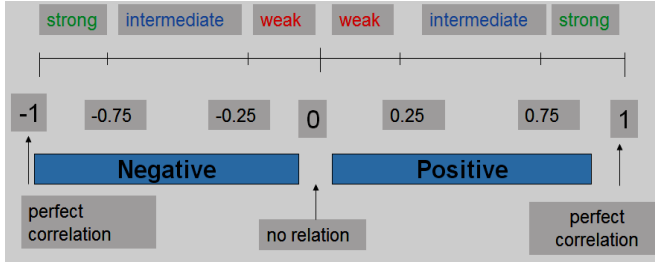


Fig.5. Possible variation of the correlation coefficient r and its interpretation

The interpretation of the letter r is the following:

“ $r = \text{zero}$ ” means no association or no correlation between the two variables, “ $0 < r < 0.25$ ” means weak correlation, “ $0.25 < r < 0.75$ ” means intermediate correlation, “ $0.75 < r < 1$ ” means strong correlation and “ $r = 1$ ” means perfect correlation.

These values can vary depending on the type of data which are examined. The mathematical formula for computing Pearson correlation coefficient r for two variables x and y is given by:

$$r = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sqrt{\left(\sum x^2 - \frac{(\sum x)^2}{n}\right) \left(\sum y^2 - \frac{(\sum y)^2}{n}\right)}} \quad (2)$$

Where x is the first variable, y the second, and n is the numbers of values x and y .

B. Calculation Example

To calculate r coefficient with two variables As_1 and As_2 , let us consider x the variable As_1 of sensor S1, y the variable As_2 of sensor S2 and n the number of loads. The tests are performed on the induction machine illustrated in Fig. 1 and presented in next section (Fig. 6). This machine has 32 rotor slots ($N^r=32$), what leads to a sensitive spectral line at 850 Hz, in corelation with the theoretical analysis which shows a polarity lower than that of the line at 750 Hz. This is reflected by a greater magnitude of the line at 850 Hz, a property which is measured experimentally [15].

The measurements of the amplitudes As_1 and As_2 for 6 loads given by sensors placed at 180° from each other around the machine are shown in Table I. These valeurs are obtained for a load increasement in healty conditions.

TABLE I. MEASUREMENT OBTAINED FROM SENSORS S1 AND S2 AROUND THE HEALTHY MACHINE

	L0	L1	L2	L3	L4	L5
$x = As_1 (\mu v)$	13.6	13.9	18.9	32	45.3	77.3
$y = As_2 (\mu v)$	14	14.1	18.5	30.4	42.7	72.9

From Equation (2) and Table I. It comes:

$$r = \frac{9278.32 - \frac{201 \cdot 192.6}{6}}{\sqrt{\left(9786.76 - \frac{(201)^2}{6}\right) \left(8798.92 - \frac{(192.6)^2}{6}\right)}} = 0.9999$$

This value $r = 0.9999$ is classified as a strong positive correlation. This means the variables vary in the same direction and there is linear correlation between the variables As_1 and As_2 .

V. EXPERIMENTAL RESULTS

This section presents experimental results obtained using induction machine characterized by 4-pole, 50 Hz, 4 kW, 380/660 V, 22.3/13A, 1450 r/min, 48 stator slots and 32 rotor bars. The induction machine illustrated in Fig.6, allows us to analyze the proposed method. There are two flux sensors placed against the machine, in the middle of the machine to reduce the influence of end windings effects. Each sensor is a circular coil constituted of 380 turns, which measures the external magnetic field around the machine.

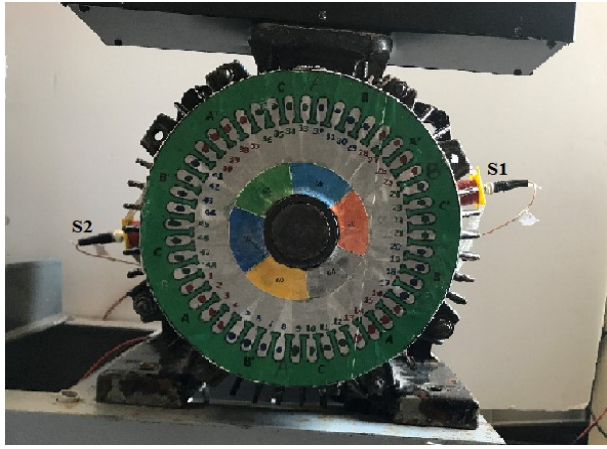


Fig.6. Induction machine with specific connector block and the flux sensors location required for the method. Flux sensors measuring the external magnetic field of IM are placed on each side of this machine

This machine allows us to simulate a damaged coil (short-circuiting coils). A rheostat is used to limit the value of short-circuit current in the stator windings. Fig.7 presents the electrical winding scheme of the induction machine as well as the connection possibilities between each winding sections.

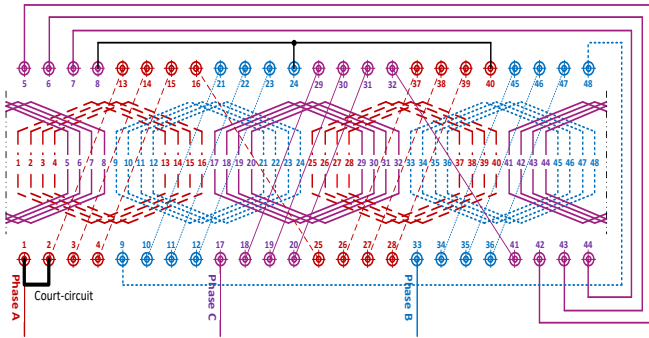


Fig.7. Electrical winding schema of induction machine

These configuration schemes allow us to short-circuit any elementary coil (turns placed in one slot) in the stator windings that corresponds to 12.5% of a full phase.

Fig.8 shows the three couples of phases coils for a 4-pole IM required to simulate a damaged coil (short-circuiting coils) using the connector block illustrated in Fig. 6.

In experimental tests, the amplitude of the harmonic at 850 Hz is analyzed considering a load increase. Different load levels, corresponding to different output powers, has been chosen in the tests with: L0=0W, L1= 128W, L2=385W, L3=750W, L4=1240W and L5= 1500W. A series of measurements is realized for each load and for different positions of short circuit realized in:

- No short-circuit.
- One fault on Phase A (short-circuits on coil 1-2).
- One fault on Phase B (short-circuits on coil 9-10).
- One fault on Phase C (short-circuits on coil 17-18).
- One fault on Phase A' (short-circuits on coil 25-26).

- One fault on Phase B' (short-circuits on coil 33-34).
- One fault on Phase C' (short-circuits on coil 41-42).

The test of all these measures has been realized with three values of the short circuit current: I1=5A, I2=10A, I3=15A.

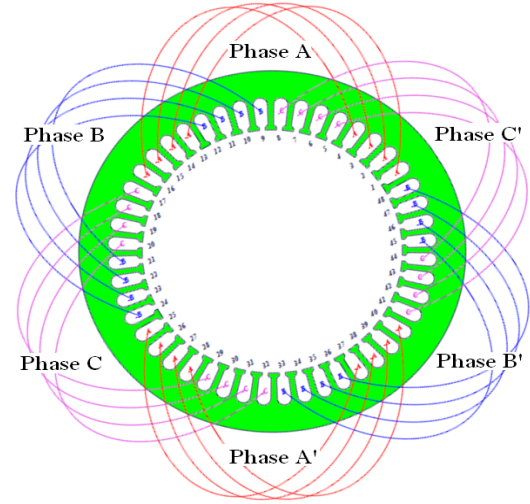


Fig.8. The three couples of phases of the induction machine.

A. Case of Sensors Placed at 180° Around the IM

Table II gives the correlation coefficient obtained for different location of short circuit and three short-circuit current.

In healthy condition of the machine, it can be observed that the correlation coefficient is very high and close to 1 (=0.9999). That represents the highest value obtained for all cases used for evaluation. In this case the relationship between the two sensors and is linear and indicates a strong positive correlation between the two variables.

In faulty condition, the magnetic dissymmetry generated by the fault leads to a difference between the signals delivered by sensors S1 and S2, and therefore between the magnitude As_1 and As_2 of the 850Hz sensitive harmonic. Then the correlation coefficient r will fall down. This can be observed in table II, where in faulty condition r decreases for all the cases relatively to the healthy cases. Actually, the value of r depends on the fault severity and the position of the short circuit in the machine relatively to the sensors location. The highest value of r is 0.9865 obtained with a 5A short circuit current, in the circuit position at P(17-18), what is close to the healthy value (0.9999). Let us analyze the influence of a threshold of r value on the efficiency of the fault detection:

- For $r_{\max} = 0.95$, the method can detect 17 faulty cases among the 18 existing 17/18.
- For $r_{\max} = 0.9$, the method can detect 14/18 faults. Here even for a fault of high severity ($I_{cc} = 15A$) one faulty case can be missed.
- For $r_{\max} = 0.85$, the method can detect 50% of the faults for the 5A short circuit case.

TABLE II. CORRELATION COEFFICIENT VALUES OBTAINED FOR SENSORS S1 AND S2 ARE PLACED IN OPPOSITION 180° AROUND OF IM

short-circuit	NO fault	I _{cc} =5A	I _{cc} =10A	I _{cc} =15A
P (1-2)	0,9999	0,9089	0,8562	0,6814
P (9-10)	0,9999	0,8686	-0,4097	0,1971
P (17-18)	0,9999	0,9865	0,8644	0,8446
P (25-26)	0,9999	0,7550	0,9423	0,9427
P (33-34)	0,9999	0,6948	-0,1060	-0,1478
P (41-42)	0,9999	-0,5642	0,5127	0,8677

Fig.9 presents the correlation coefficient values obtained when the sensors S1 and S2 are placed in opposition (at 180°) around of IM. We can remark a decrease of correlation coefficient for each short-circuit position which generally decreases with the increase of the I_{cc} current. For some positions corresponding to a “good” positioning of the sensor related to short-circuit position this coefficient can turn into negative value.

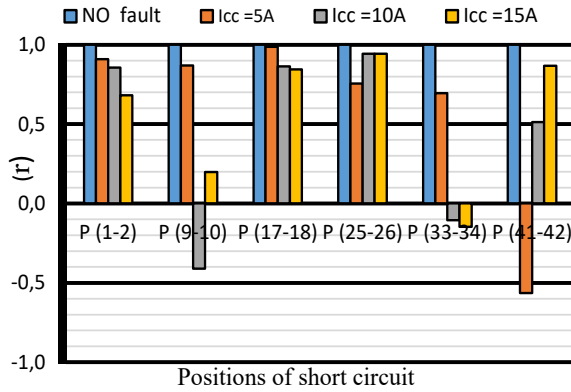


Fig.9. The values of correlation coefficient when the sensors S1 and S2 are placed at 180° around of IM.

B. Case of Sensors not Placed at 180° Around the IM

This section presents results obtained with if sensors S1 and S2 are not correctly placed symmetrically from each other. Here, they are placed at 160° around the IM as shown in Fig.10. The Table III gives the evolution of the correlation coefficient.

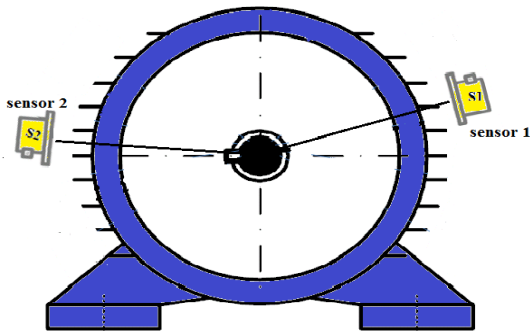


Fig.10. Position of sensors S1 and S2 not placed at 180° around the induction machine

TABLE III. CORRELATION COEFFICIENT VALUES OBTAINED FOR SENSORS S1 AND S2 ARE NOT PLACED IN OPPOSITION 180° AROUND OF IM

short-circuit	NO fault	I _{cc} =5A	I _{cc} =10A	I _{cc} =15A
P (1-2)	0,9355	0,9230	0,5381	0,7356
P (9-10)	0,9355	0,9964	0,8436	0,9973
P (17-18)	0,9355	0,9248	0,9425	0,9901
P (25-26)	0,9355	0,9481	0,5203	0,9667
P (33-34)	0,9355	0,9532	-0,3941	-0,4057
P (41-42)	0,9355	0,9731	0,6573	0,7380

For this case it can be observed that in healthy condition of the machine, the correlation coefficient is now $r = 0.9355$ and in some faulty cases it is observed that the correlation coefficient can be highest that the value obtained in the healthy case even for high severity fault. Let us analyze again the influence of a threshold of r value on the efficiency of fault detection.

- For $r_{max} = 0.95$, the healthy case is considered as a faulty one. In this case, the method can detect 12/18 detect.
- For $r_{max} = 0.9$, the method can detect only 8/18 cases, that corresponds to less than 50% of the fault cases, for I_{cc} =5A none of the faults are detected.
- For $r_{max} = 0.85$, the method allow us to detect 8/18 case.

As for the last threshold, the method can detect only 50% of the faults cases.

It is clear that sensors misalignment leads to a strong degradation of the fault detection. The evolution of the correlation coefficient obtained for sensors S1 and S2 are placed in opposition at 160° around of IM is shown in Fig.11.

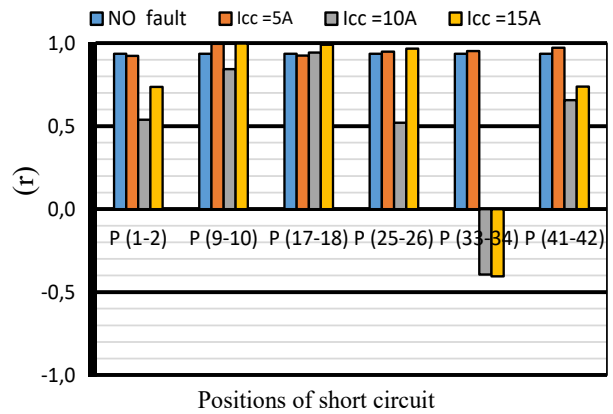


Fig. 11. The values of correlation coefficient for sensors S1 and S2 are not place at 180° from other around the IM

This comparative analysis between the cases when the sensors at placed at 180° and 160° around of IM helps us to conclude that the method requires an accurate set up of sensors position to be efficient. To facilitate the interpretation of the results all measurements concerning the IM are presented as “the harmonic defined at 850 Hz” but in reality, the increase of

the load leads to a sliding value of this harmonic, which decrease with the load increase.

VI. CONCLUSION

In this paper, a new method is presented for the diagnosis of an inter-turn short circuit in the stator winding of electrical machines. It uses an analysis of the external magnetic field. The advantage of the proposed method is that it is reliable, inexpensive and simple to implement. This noninvasive method uses two flux coil sensors diametrically located to measure the external magnetic field in the vicinity of the machine. Pearson correlation coefficient is proved to be a useful tool for detecting a fault in the induction machine. Moreover, the method has a high-level accuracy and speed for the faults detection. On the other hand this method does not require any knowledge on the presumed healthy state of the machine. A difference of values of the Pearson correlation coefficient is a good indicator of inter-turn short circuit fault.

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