

An improvement of a diagnosis procedure for AC machines using two external flux sensors based on a fusion process with belief functions

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Abstract- In this paper, a method for diagnosis of AC machines using the spectrum of the near magnetic field is presented. The method is associated to a fusion process based on belief functions which analyze these measurements. In previous works, it has been shown that it was possible to detect the inter-turns short circuit in the stator windings of electrical machines using a noninvasive method. It is based on the analysis of the variation of sensitive harmonics when the load varies, and eliminates the main drawback presented by other diagnostic methods which use the comparison with a healthy state assumed known. Several measurements around the machine are necessary to increase the probability of the fault detection because the fault position relatively to the sensor can strongly influence the results. So in this paper it is proposed to exploit conjointly all the measurements in order to obtain a more robust and reliable diagnostic and to increase the probability of detecting the fault. The merging of the different estimations being realized through the belief functions framework, this approach is tested on real measurements. Experimental tests are performed on a special rewound induction machine in order to validate the theoretical approach.

I. INTRODUCTION

In order to increase the systems productivity and safety of industrial applications it is interesting to use the diagnosis methods and to anticipate the motors failure. Diagnosis and fault detection of electrical machines are in the scope of these matter and require the development of measurement, acquisition, analysis techniques and decision support.

Over the last decade different techniques have been developed and the technology of this field is still in permanent evolution. The techniques such as those based on the analysis of vibrations or currents [1-3] have already proven beyond the scope of the research laboratories that they can find their place in an industrial environment. However, the interpretation of results requires a high expertise level and are expensive, making it difficult to a real democratization of these techniques. Actually only the systems where a breakdown of the machine can have disastrous consequences are equipped with a monitoring system (for example in power generation plants).

Recently, methods based on the analysis of external magnetic field have been developed; their advantages are the noninvasive investigation and simplicity of implementation [4-6]. For many industrial applications it is interesting to use the noninvasive measurement methods to detect the faults of electrical machines without stopping the operation. However, all the diagnostic methods usually require the knowledge of the machine's healthy state regardless of the used physical quantity [7-9]. The fault detection is then based on the

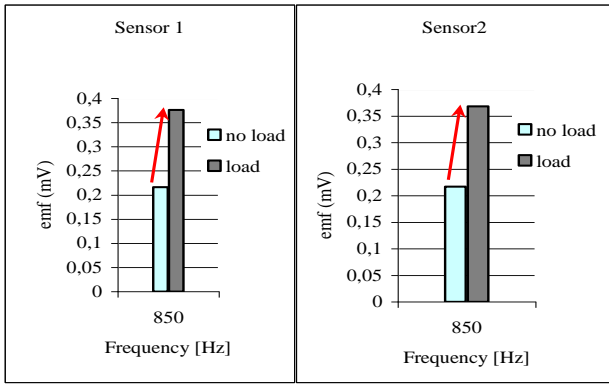
comparison of the signature for a given state with this of the presumed healthy state by considering an indicator issue from a measurement that is known to be sensitive to a fault. The difficulty lies in the fact that the healthy state is practically never known until the failure occurs because the user of the machine did not record the healthy signature. In the same time, in generally, the load is a disturbing factor for diagnosis because it induces several healthy states.

The aim of this paper is to propose a diagnosis procedure for an induction machine using two external flux sensors and based on a fusion process with belief functions. The method exploits the variation with load of sensitive spectral lines instead of their magnitude itself. The paper is organized as follows. The next section recalls some principles of the diagnosis procedures. Basic concepts on the belief function theory are presented in the third section. Then a fusion process for fault diagnosis is developed and tested in fourth section. In order to demonstrate the validity of this method the experimental results were presented in fifth part. Finally a discussion and the presentation of future works conclude the paper.

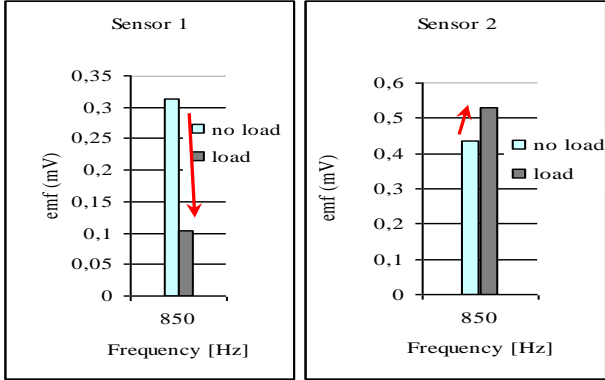
II. DIAGNOSIS PROCEDURE

The originality of the non-invasive diagnosis method presented in [10] is the use of the load to perform the fault detection (the load is not longer a disturbing factor). Furthermore, the method does not require the knowledge of the machine's healthy state. A comparison between machine operating conditions (no-load and load) enables to detect a stator fault. For diagnosis two flux sensors, placed on each side of the machine which measures the external magnetic field of the machine, are used [11]. The method consists in comparing the signals delivered by each sensor in function of the load variation (Fig. 1). More precisely, the procedure uses the magnitude variations of a specific sensitive harmonic depending on the type of machine especially its number of rotor slots. For Induction Machine (IM) used in experimental tests the harmonic 850 Hz is analyzed. Considering a load increase, the method principle can be described in the following way:

- if the sensitive harmonic amplitudes measured by the sensors vary in the same direction, then no fault is suspected, (Fig. 1-a)
- otherwise (they vary in opposite directions), a fault (a inter-turns short circuit in the stator windings) is suspected (Fig. 1-b).



a) no faulty case



b) faulty case

Fig. 1. Harmonic amplitude variation in load and no load case for no faulty and faulty case.

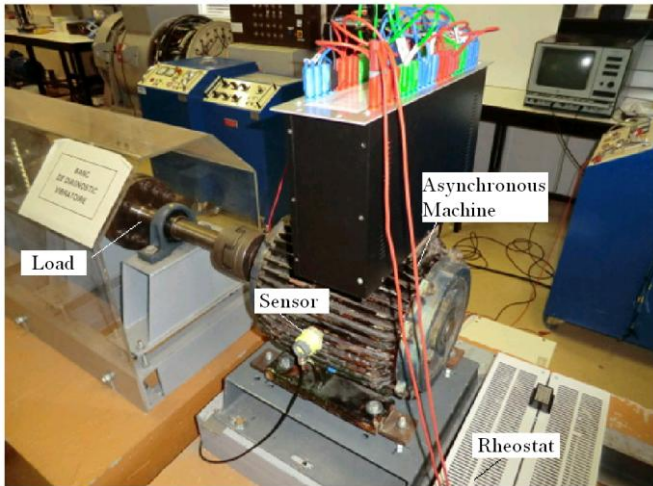


Fig. 2. Testbed used for the experiments. Flux sensors measuring the external magnetic field of the 3-phase induction machine are placed on each side of this machine. The equipment above the machine allows one to simulate a fault by short-circuiting coils. The machine can run under no-load or loading conditions.

A testbed, illustrated in Fig. 2, allows us to test this method on a 3-phase induction machine. The machine has been rewound and all the elementary sections are extract in order to create short-circuit faults at different position of the stator winding. Then, different measurements on each sensor are obtained for different load conditions.

Experimental results have shown that the proposed procedure does not lead to a good decision when the sensors are not placed just in front of the faulty phase. Consequently it is necessary to analyze data from several positions to improve the diagnosis. Of course, it is not possible to cover

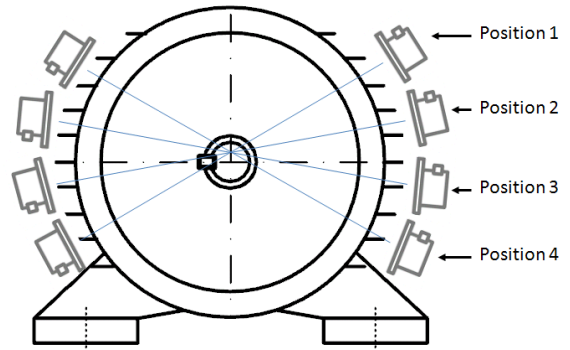


Fig. 3. Illustration of the four possible positions for the two sensors to detect a fault.

the whole periphery of the machine, as it should be ideally, so measurement are limited to 4 twins of positions as depicted in Fig. 3.

In this paper, different strategies are investigated to improve the method. Firstly, measurements will be partially considered as the difference of amplitudes between sensors measurements tends to be significant in case of a fault, while measurements tend to be similar with no fault.

Secondly, to manage the fusion and the imperfection of the measurements, a model based on the belief function theory [12, 13] has been introduced. This theory which generalizes in particular the probability theory, allows one to exploit conjointly, several imperfect sources of information to make proper decision.

III. BELIEF FUNCTION THEORY: BASIC CONCEPTS

A. Information Representation

Let us consider a finite set Ω composed of the possible values of a variable of interest \mathbf{x} . We do not know the true value taken by \mathbf{x} , but we have information regarding this value given by different sources of information, each piece of information being represented by a mass functions m .

Formally, a mass function m defined on $\Omega = \{\omega_1, \dots, \omega_K\}$ (called the frame of discernment) is an application from 2^Ω to $[0,1]$ verifying:

$$\sum_{A \subseteq \Omega} m(A) = 1 \quad (1)$$

For each subset A of Ω , the quantity $m(A)$ represents the part of the unit mass allocated to the hypothesis that the true value of \mathbf{x} lies in the subset A of Ω , and in no strict subsets.

For example, let us consider a coin tossing with $\Omega = \{\text{heads}, \text{tails}\}$. We have no information regarding the fact that the coin is fair or biased. Thus our knowledge is represented by $m(\{\text{heads}, \text{tails}\})=1$ (a total ignorance state), neither $\{\text{heads}\}$ nor $\{\text{tails}\}$ receives a strictly positive mass.

B. Manipulating Information

Suppose that we receive two pieces of information quantified by m_1 and m_2 , both expressed on Ω , coming from two distinct sources. These two mass functions can be combined using the conjunctive rule of combination defined by:

$$m_1 \cap m_2(A) = \sum_{B \cap C = A} m_1(B) m_2(C), \quad \forall A \subseteq \Omega \quad (2)$$

This combination is associative and commutative, which ensures that the order the sources are combined does not affect the combination result. Its neutral element is the mass function representing the total ignorance: $m(\Omega)=1$.

For example, let us consider a frame $\Omega = \{\omega_1, \omega_2\}$, and two sources of information S_1 and S_2 providing two mass functions m_1 and m_2 defined by $m_1(\{\omega_2\}) = 0.2$, $m_1(\Omega) = 0.8$, $m_2(\{\omega_2\}) = 0.3$ and $m_2(\Omega) = 0.7$. The conjunctive combination of m_1 and m_2 is then given in Table 1. The resulting mass function, denoted m , is therefore defined by $m(\{\omega_2\}) = 0.06 + 0.14 + 0.24 = 0.44$, and $m(\Omega) = 0.56$. The mass supporting ω_2 has then been reinforced with this combination.

TABLE I
CONJUNCTIVE COMBINATION OF TWO MASS FUNCTIONS

$m_1 \setminus m_2$	$\{\omega_2\}$ 0.3	Ω 0.7
$\{\omega_2\}$ 0.2	$\{\omega_2\} \cap \{\omega_2\} = \{\omega_2\}$ $0.2 \times 0.3 = 0.06$	$\{\omega_2\} \cap \Omega = \{\omega_2\}$ $0.2 \times 0.7 = 0.14$
Ω 0.8	$\Omega \cap \{\omega_2\} = \{\omega_2\}$ $0.8 \times 0.3 = 0.24$	$\Omega \cap \Omega = \Omega$ $0.8 \times 0.7 = 0.56$

C. Decision Making

When a decision has to be made regarding the true value of \mathbf{x} , a strategy [13, 14] consists in transforming the mass function m , resulting from the fusion process, into the following probability measure $BetP$, called the *pignistic probability* and defined by:

$$BetP(\{\omega\}) = \sum_{\omega \in A, A \subseteq \Omega} \frac{m(A)}{|A| (1 - m(\emptyset))}, \quad \forall \omega \in \Omega \quad (3)$$

The chosen decision is then the one that maximizes $BetP$. The resulting pignistic probability associated with the combined mass function m depicted in Table 1 is defined by: $BetP(\{\omega_1\}) = 0.56/2 = 0.28$ and $BetP(\{\omega_2\}) = 0.44 + 0.56/2 = 0.72$. It follows a decision in favor of ω_2 .

IV. FUSION PROCESS FOR FAULT DIAGNOSIS

In the present application, the main question of interest is “Is there a fault?”. Let us then define a variable of interest \mathbf{x} which takes its values in $\Omega = \{y, n\}$, “y” standing for “yes there is a fault” and “n” for “no, there is no fault”.

To detect a fault, four positions on the machine have been chosen (Fig. 3). Measurements of the two sensors taken at these positions are then considered as pieces of evidence regarding the fact that there is a fault on the machine.

A difficult part when modeling a fusion process with belief functions is to define masses values.

This can be done by a learning set composed of labeled data (measurements are obtained while the truth is known) and by experts’ opinions. Both have been used in this paper.

As illustrated in Fig. 4, the three couples of phases has been called A-A’, B-B’ and C-C’, and each stator slot has a number. For example, stator slots 1, 2 are coils of phase A. Tests are carried out on an **IM** characterized by: 11kW, 50Hz, $p=4$, 380/660V, $N^s=48$ and $N^r=32$. This machine has been rewounded such that the terminals of the different stator elementary sections are extracted from the winding and are brought back to a connector block, which is fixed above the machine as indicated in Fig. 2. This machine allows us to simulate a damaged coil (short-circuiting coils), for example coils 1-2, corresponding to 12.5% coils of phase A. Using the testbed (Fig. 2.) we can then obtained measures from the sensors in each of the position 1, 2, 3 and 4 depicted in Fig. 3, for different loads, and for different simulated faults. A rheostat is used to limit the value of short-circuit current in elementary coil.

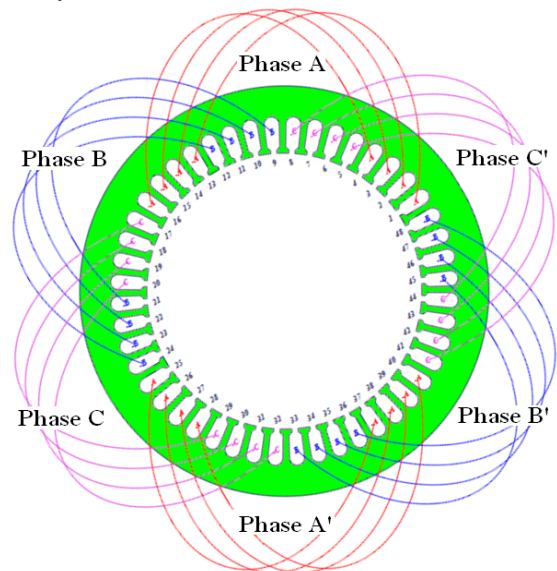


Fig. 4. The three couples of phases of the asynchronous machine. Short-circuits can be made on each elementary coil using the connector block illustrated in Fig. 2.

Loads increase has been chosen equal to 0 (no load), 600W, 1000W and 1400W. A series of measurements for each of these loads and each of the positions (Fig.3) has then been realized with:

- no fault,
- two faults on Phase A (short-circuits on coils 1-2 then 1-3),
- two faults on Phase B (short-circuits on coils 9-10 then 9-11),
- two faults on Phase C (short-circuits on coils 17-18 then 17-19)
- two faults on Phase A’ (short-circuits on coils 25-26 then 25-27)
- two faults on Phase B’ (short-circuits on coils 33-34 then 33-35)

- two faults on Phase B' (short-circuits on coils 41-42 then 41-43)

These series of measurements constitutes the learning set. Table II shows the measurements obtained with the two sensors placed in position 2 on a machine with no fault. Columns "Sensor i evolution" (with $i=1,2$) indicate respectively the difference between sensor i measurement obtained at the current load with the measurement obtained at the previous load (for example $160 = 376 - 216$). It can be observed that sensors measurements increase with the loads. As there is no fault, this behavior was expected.

A different situation is exposed in Table III. The machine has a fault (short-circuit 1-3), but as sensors measurements evolutions are different (two times: between loads 0 and 600 and between loads 1000 and 1400).

However this is not always the case as illustrated by the example exposed in Table IV. In this situation, there is a fault (short-circuit 1-2) but there is no difference of evolution between sensors measurements: both sensors measurements increase while the load increases.

TABLE II
MEASUREMENTS OBTAINED FROM SENSORS 1 AND 2 IN POSITION 2 ON A MACHINE WITH NO FAULT.

Load (W)	Sensor 1 (μV)	Sensor 1 Evolution	Sensor 2 (μV)	Sensor 2 Evolution	Same evolution?
0	216		217		
600	376	160	368	151	yes
1000	478	102	470	102	yes
1400	531	53	526	56	yes

TABLE III
MEASUREMENTS OBTAINED FROM SENSORS 1 AND 2 IN POSITION 2 ON A MACHINE WITH SHORT-CIRCUIT ON COILS 1-3 ON PHASE A. SITUATIONS WHERE SENSORS MEASUREMENTS VARY IN AN OPPOSITE WAY ARE IN BOLD.

Load (W)	Sensor 1 (μV)	Sensor 1 Evolution	Sensor 2 (μV)	Sensor 2 Evolution	Same evolution?
0	314		436		
600	103	-211	529	93	no
1000	338	235	615	86	yes
1400	503	165	596	-19	no

TABLE IV
MEASUREMENTS OBTAINED FROM SENSORS 1 AND 2 IN POSITION 2 ON A MACHINE WITH SHORT-CIRCUIT ON COILS 1-2 ON PHASE A).

Load (W)	Sensor 1 (μV)	Sensor 1 Evolution	Sensor 2 (μV)	Sensor 2 Evolution	Same evolution?
0	146		226		
600	245	99	436	210	yes
1000	348	103	573	137	yes
1400	456	108	737	164	yes

The set of all the results are regrouped on Table V. For example, we retrieve that in position 2, with a 1-3 fault two

different evolutions were found. As a difference of evolution is a sign of a fault, it is sufficient to detect a fault in one position to ensure that there is a fault on the machine. However this strategy is not sufficient to detect short-circuits 1-2 and 25-26 (see Table V zero different evolution for each position).

TABLE V
NUMBER OF DIFFERENT EVOLUTIONS DETECTED IN FUNCTION OF THE POSITION AND THE FAULT IN THE LEARNING SET (IN BOLD THE CASES WHERE THE FAULT HAS NOT BEEN DETECTED).

	Position 1	Position 2	Position 3	Position 4
No fault	0	0	0	0
1-2	0	0	0	0
1-3	3	2	3	1
9-10	0	0	1	1
9-11	0	0	0	1
17-18	1	0	0	0
17-19	1	2	2	3
25-26	0	0	0	0
25-27	2	1	0	0
33-34	1	1	2	0
33-35	1	0	2	3
41-42	1	0	0	0
41-43	2	3	3	3

Thus values measurements have been considered too. Indeed, it has been observed that the absolute value of the difference between sensor 1 measurement and sensor 2 measurement tends to be greater in case of a faulty machine than in case of a healthy machine. Results in Table VI give examples in situations with no fault, a fault in position 1-2 and a fault in position 1-3.

TABLE VI
ABSOLUTE VALUES OF THE DIFFERENCES OF MEASUREMENTS BETWEEN SENSOR 1 AND 2 IN EACH SITUATION DESCRIBED IN TABLE II (NO FAULT), TABLE III (FAULT 1-3) AND TABLE IV (FAULT 1-2).

Load (W)	Dif. with no fault (Table II) (μV)	Dif. with fault 1-2 (Table IV) (μV)	Dif. with fault 1-3 (Table III) (μV)
0	1	80	122
600	8	191	426
1000	8	225	277
1400	5	281	93

To exploit jointly all these pieces of information (sensors measurements difference of evolutions and sensors measurements absolute values in each position), a model based on mass functions has been developed. As previously explained the frame of discernment is chosen equal to $\Omega=\{y,n\}$. Eight pieces of evidence are to be quantified: the differences of evolution in positions 1 to 4, and measurements values in positions 1 to 4.

In case of a difference of evolution, a fault is surely present, then masses regarding the presence of a fault in position i ($i=1,2,3,4$) are initialized in the following way:

V. EXPERIMENTS

- If there is at least a difference of evolution: $m_{\text{evo},i}(\{y\})=0,95$ and $m_{\text{evo},i}(\Omega)=0,05$. It represents the fact that there is surely a fault.
- If there no opposite evolution in the measurement: $m_{\text{evo},i}(\{n\})=0,05$ and $m_{\text{evo},i}(\Omega)=0,95$. We do not know if there is a fault, however there is a small chance that there is no fault. The pignistic probability associated with this mass function is near a 50-50 biased in favor of no fault.

It remains to take into account measurements values in position i ($i=1,2,3,4$). The main idea is that with no fault sensors, measurements are rather close, while with a fault the difference between these values tends to widen. Thus masses are chosen in the following manner:

- If the maximum of the absolute values of the differences is lower than 200: $m_{\text{val},i}(\{n\})=0,05$ and $m_{\text{val},i}(\Omega)=0,95$ (we do not know if there is a fault, maybe not).
- If this value is between 200 and 300, we start to think that maybe there is a fault: $m_{\text{val},i}(\{y\})=0,05$ and $m_{\text{val},i}(\Omega)=0,95$ (but we remain doubtful).
- With this difference between 300 and 500, a fault is more credible: $m_{\text{val},i}(\{y\})=0,5$ and $m_{\text{val},i}(\Omega)=0,5$.
- At last if the difference is greater than 500, a fault is more surely present: $m_{\text{val},i}(\{y\})=0,8$ and $m_{\text{val},i}(\Omega)=0,2$.

Even if it has been seen in Table VI that with no fault the absolute values of the differences are much smaller than 300, a diagnosis method with a complete knowledge of a healthy machine is not expected. This is the reason why only a cautious allocation of the masses has been realized.

For example, information in Table II are then quantified by $m_{\text{evo},2}(\{n\})=0,05$ and $m_{\text{evo},2}(\Omega)=0,95$ as there is no opposite evolutions, while information in Table III give the following knowledge: $m_{\text{evo},2}(\{y\})=0,95$ and $m_{\text{evo},2}(\Omega)=0,05$. Results exposed in Table VI induce the following information:

- For the scenario exposed in Table II (the maximum value of the absolute values of the differences is equal to 8): $m_{\text{val},2}(\{n\})=0,05$ and $m_{\text{val},2}(\Omega)=0,95$
- For the scenario exposed in Table IV (the maximum is equal to 281): $m_{\text{val},2}(\{y\})=0,05$ and $m_{\text{val},2}(\Omega)=0,95$
- For the scenario exposed in Table III (the maximum being equal to 426): $m_{\text{val},2}(\{y\})=0,5$ and $m_{\text{val},2}(\Omega)=0,5$.

Once the mass functions initialized, the next step consists in the fusion of the mass functions using the conjunctive rule of combination (Eq. 2). The chosen decision is then the one that maximizes the pignistic probability (Eq. 3).

The proposed method for fault diagnosis can then be summarized in the following manner:

1. For each position i ($i=1,2,3,4$) illustrated in Fig. 3, from the measurements obtained from sensors, compute $m_{\text{evo},i}$ and $m_{\text{val},i}$
2. Combine conjunctively all the mass functions: $\bigcap_{i=1,2,3,4} m_{\text{evo},i} \bigcap \bigcap_{i=1,2,3,4} m_{\text{val},i}$
3. The probability of having a fault is then given by $\text{BetP}(\{y\})$.

To test this fusion process, three new series (called series 2, 3 and 4) of measurements have been undertaken under the same conditions, with the same machine and testbed (Fig. 2).

Pignistic probabilities obtained from a combination of only the information regarding the opposite evolutions of measurements are depicted in Fig. 5.

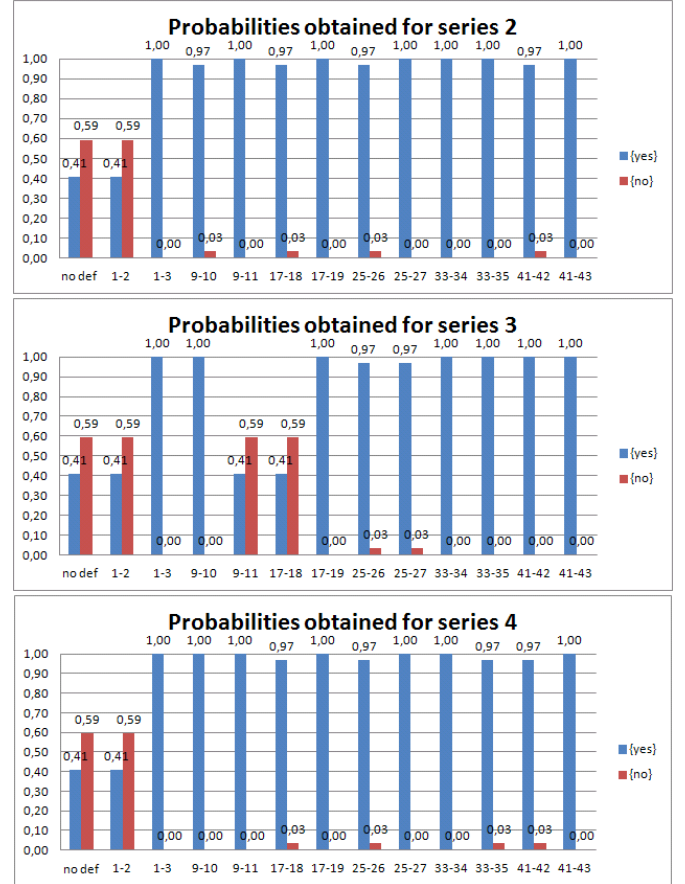


Fig. 5. Probabilities of fault obtained with the fusion of only information regarding the opposite evolutions of measurements in each position ($m_{\text{evo},i}$ with $i=1,2,3,4$).

These probabilities are obtained from the pignistic transformation of the conjunctive combination of mass functions $m_{\text{evo},i}$ with $i=1,2,3,4$.

Pignistic probabilities obtained from the combination of all the mass functions $m_{\text{evo},i}$ and $m_{\text{val},i}$ with $i=1,2,3,4$ are illustrated in Fig. 6.

In series 2 and 4 (Fig.5 and Fig.6), the probability of a fault is strictly greater than 0,5 (a fault is detected) in each case except when the machine has no fault (indicated as “no def” below the first histogram) and when there is a fault in position 1-2. Thus the two fusion process has obtained the same results in these series. The consideration of measurements values has not improved the diagnosis.

In series 3 (Fig.5 and Fig.6), the second strategy has allowed the detection of faults in position 1-2 (Phase A), 9-11 (Phase B) and 17-18 (Phase C) which were not detected by just considering the opposite evolutions of measurements.

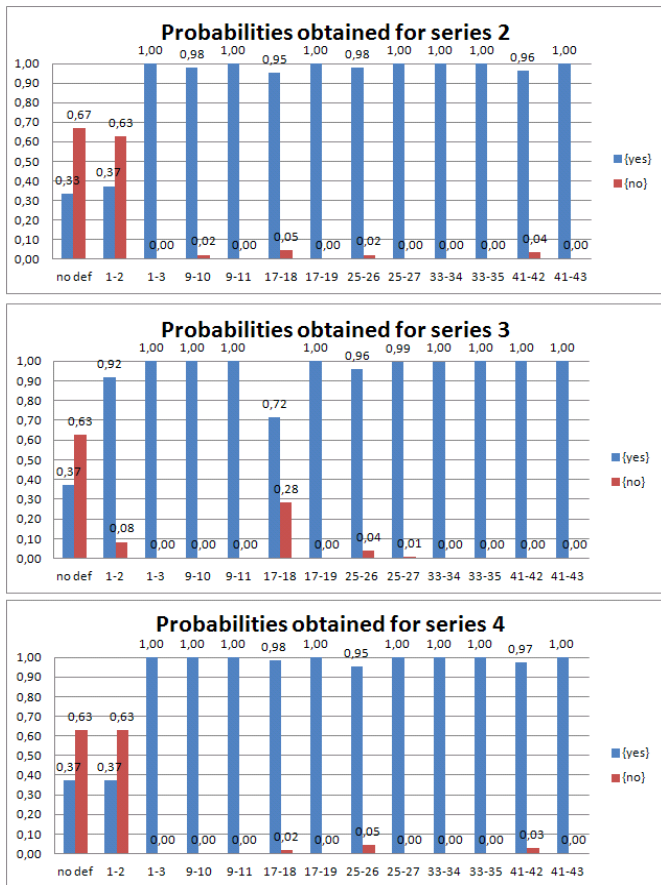


Fig. 6. Probabilities of fault obtained with the fusion of all the mass functions $m_{\text{evo},i}$ and $m_{\text{val},i}$ with $i=1,2,3,4$.

Then in this series, information regarding the measurements values have been useful.

Finally if we regroup the results obtained from these three series, over the 39 decisions to make, the fusion process taking into account only the opposite evolutions of measurements has realized 34 good decisions (~87,2%) and the fusion considering also measurements values has made 37 good decisions (~94,9%).

VI. CONCLUSION

This paper use conjointly a non-invasive diagnosis approach and an approach based on a stochastic model (belief functions) to diagnose the inter-turns short circuit in the stator windings of electrical machines. Both approaches provide an interpretation of the magnetic field variation outside the machine in the presence of a fault, without need to know the healthy state of the machine, the comparison being made between two states of working (called 'no load and in load case). The method proposes to exploit the measured values of the external magnetic field, obtained by a specific sensor in order to increase the probability of finding the fault. Direct analysis of the spectrum corresponding to the external magnetic field may determine the fault of the machine. However the information provided by the sensors are dependent on the position of each one in relation to fault, the load level of the machine and the fault severity, hence the interest of a statistical method which takes into account these

parameters. By applying a conjointly analysis between the two methods it has enabled this work to increase the detection probability of the fault from a value of ~87,2% to ~94,9%.

VII. DISCUSSION AND FUTURE WORKS

Let us point out that the amplitude of the measured harmonics strongly depends on the fault severity and the location of the sensor in relation to the machine. So in this paper, four sets of measurements were used for each sensor position and four positions of sensors around the machine. The uses of two jointly approaches have yielded a significant probability for determining the machine fault. It will be interesting to know the evolution of the probability with increasing the number and positions of measurements in order to establish a protocol for industrial implementation. This will be the next step of this study.

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