Information fusion of external flux sensors for detection of inter-turn short circuit faults in induction machines

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***Abstract* - This paper presents a method based on fusion technique applied to signatures obtained from external stray flux to detect an inter turn short circuits in induction machines. This technique uses the belief functions framework to represent and merge the information about short circuits obtained from sensors placed around the machine to be diagnosed. The influence of the sensors positions around the machine to detect faults is studied. This fusion technique leads to a new diagnosis method, which only uses the information captured from the stray magnetic field around the machine, having then the advantage of being non-invasive. Six external flux sensors placed on a belt fixed around the machine provide information used for the diagnostic technique. These signatures are obtained by experimental tests using a rewound induction machine that allows one to create inter-turn short circuit faults with different severity levels.**

Keywords - Asynchronous machine, belief function, fault detection, magnetic field, inter-turn winding fault, flux measurement.

I. INTRODUCTION

Due to the technological developments, the three-phase induction machine (**IM**) has become popular in industry do to its robustness, low cost, low maintenance, high power density and good performances. However, this machine is subjected to many undesirable stresses, which can cause stator and rotor faults, or other failures. The majority of these failures are related to bearings (41%), winding (37%), rotor faults (10%) and others (12%) [1-3]. In practice, it is important to detect these faults at an early stage for safety operations of these machine, because failures can lead to poor efficiency, more energy consumption and unexpected stop of the system. Early detection of winding faults is then essential for many industrial applications. Moreover, for specific applications it is interesting to use fully noninvasive measurement methods to detect faults in electrical machines without stopping or modifying the operation systems [4, 5]. Fault diagnosis of rotating electrical machines has received an intense amount of research interest during the last 30 years [6]. Several diagnosis methods, based on time domain or frequency domain analysis, have been proposed to detect rotor failures using techniques such as Instantaneous Frequency (IF) [7] or Motor Square Current Signature Analysis (MSCSA) [8]. The detection of inter-turn short-circuits fault in electrical machines is generally based on stator current analysis, associated to different methods as Improved Artificial Ant Clustering Technique [9], Square Current Space-vector Signature Analysis (SCSSA) [10], Artificial Neural Network (ANN) [11]. Methods based on Time Series Data Mining (TSDM) has also been developed [12].

These techniques can detect faults in electrical machines but their implementation requires complex data acquisition equipment, sometime additional measurements, and takes a relatively long time [13]. Moreover, usual diagnostic methods generally require the knowledge of the healthy state of the machine regardless of the measured physical variable [4, 5].

This paper presents a diagnostic method, which does not require the knowledge of the machine healthy state. It is based on measurements of external magnetic field around the electrical machine using bound flux sensors [5, 14]. By performing the measurements at three positions P1 (S1- S4), P2 (S2- S5), P3 (S3- S6), as shown in Fig.1 and analyzing and merging information from sensors with the belief function theory [4], it is possible to obtain a good probability of diagnosis. In the literature [14] it is mentioned that the analysis of external stray flux is more sensitive to current signature analysis as far as the stator inter-turn short-circuit fault is concerned. However the weakness of the diagnosis methods based on external flux measurement is that the acquired signal is strongly dependent on the position of the sensors around the motor relatively to the fault location. So in order to assess the reliability of the method proposed in this paper, we analyze the influence of sensor positions around the machine in terms of probability of diagnosis.

The paper is organized as follows. Section II introduces basic concepts of belief function theory applied to data coming from coil sensors placed in three positions around an induction machine. Section III gives the proposed technique for the acquired signals and presents the fusion method with considered mass functions used for the processing of the measured signals. Section IV presents experimental results and discussion and Section V concludes the paper.

II. Basic Concepts on Belief Functions

Basic concepts on belief functions used in this paper are exposed in this Section. Belief functions are an expressive and flexible framework allowing the representation and the handling of uncertain and imprecise information.

A. Information representation

Let us consider a question Q of interest whose answers are in a finite set $\Omega = \{\omega_1, \ldots, \omega_K\}$ called the frame of discernment or universe of discourse. A piece of information regarding the answer of Q can be represented by a Mass Function (MF) m defined as an application from the power set of Ω denoted by:
$2^\Omega = \{A | A \subseteq \Omega\} = \{\phi, \{\omega_1\}, \{\omega_2\}, \{\omega_1, \omega_2\}, \ldots\}$ to [0, 1] such that the sum of the masses is equal to one

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

With A a subset of Ω, a mass $m(A)$ represents the degree of knowledge in favor of the fact that the answer to Q belongs to A. The mass $m(\Omega)$ represents the degree of total ignorance regarding the answer to question Q, especially $m(\Omega)$ =1 represents the total ignorance (it only indicates that the answer to Q is in Ω what was already given).

B. Combining evidence

Two pieces of information represented respectively by MFs m_1 and m_2, and coming from two distinct sources, can be combined using the Conjunctive Rule of Combination (CRC) [15, 16] 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 rule being associative and commutative, the order considered for combined sources does not affect the combination result.

Let us consider as an example a very simple diagnostic problem with a frame Ω composed of two elements y and n, $\Omega = \{y, n\}$, where "y" means "yes, there is a fault in the inspected winding" and "n" meaning "no, there is not faults". Let us suppose two independent and reliable experts E_1 and E_2 expressing their opinions regarding the presence of a fault with, respectively, the two following MFs m_1 and m_2 defined, respectively, by $m_1(\{y\}) = 0.1$, $m_1(\Omega) = 0.9$, $m_2(\{y\}) = 0.2$ and $m_2(\Omega) = 0.8$. Both experts are then rather not sure of the presence of a fault. A large mass (90% for expert E_1 and 80% for expert E_2) is on the ignorance regarding the fact that there is a fault.

The combination or fusion, denoted by m , of pieces of information m_1 and m_2 using CRC rule (2) is illustrated in Table I and given by $m(\{y\}) = 0.02 + 0.08 + 0.18 = 0.28$, and $m(\Omega) = 0.72$. The mass supporting the fact that there is a fault has then been reinforced using the CRC rule.

TABLE I. Conjunctive Combination of Mass Functions m_1 and m_2

m_1 \ m_2	$\{y\}$ 0.2	Ω 0.8
$\{y\}$ 0.1	$\{y\} \cap \{y\} = \{y\}$ $0.1 \times 0.2 = 0.02$	$\{y\} \cap \Omega = \{y\}$ $0.1 \times 0.8 = 0.08$
Ω 0.9	$\Omega \cap \{y\} = \{y\}$ $0.9 \times 0.2 = 0.18$	$\Omega \cap \Omega = \Omega$ $0.9 \times 0.8 = 0.72$

C. Decision Making

Once the available information regarding the answer to question Q is summed up by a single MF m, a manner to make a decision [15, 17] consists in transforming m into the following probability measure $BetP$ 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 maximizing $BetP$. As an example, the probability $BetP$ associated with m depicted in Table I is given by:

$$BetP(\{y\}) = m(\{y\}) + m(\{y,n\})/2 = 0.28 + 0.72/2 = 0.64$$

and

$$BetP(\{n\}) = m(\{n\}) + m(\{y,n\})/2 = 0 + 0.72/2 = 0.36$$

The chosen decision, which maximizes $BetP$, is then the one in favor of "y" meaning "there is a fault".

III. External Flux Measurement and Fusion Methode for Diagnosis

This section exposes how measurements coming from six flux sensors placed at different positions around the frame of an induction machine are used to indicate the presence of a fault as shown in Fig.1.

A. Proposed technique for signals measurement

For IM used in experimental tests the magnitude of the harmonic 850Hz sensitive to the fault [5] is considered for the analysis. The variation with the load of the amplitude for each diametrically opposite pair of sensors is compared. Let S_2 and S_5 two diametrically opposed sensors. Considering a load increase, the principle of the method can be described as follows:

- if the sensitive harmonic amplitudes measured by the sensors vary in the same direction after load change then no fault is suspected. This case is presented in Fig. 2

where no load (NO) and five different loads are considered. We can remark here quasi identically amplitude variation for sensors S2, S5 and the same difference of variation [4].

- otherwise (they vary in opposite directions as presented in Fig. 3), a fault (an inter-turns short circuit in the stator winding) is suspected. In this case, a difference between the amplitude of the sensors S2, S5 appears and this parameter allows one to calculate the ratio of amplitudes.

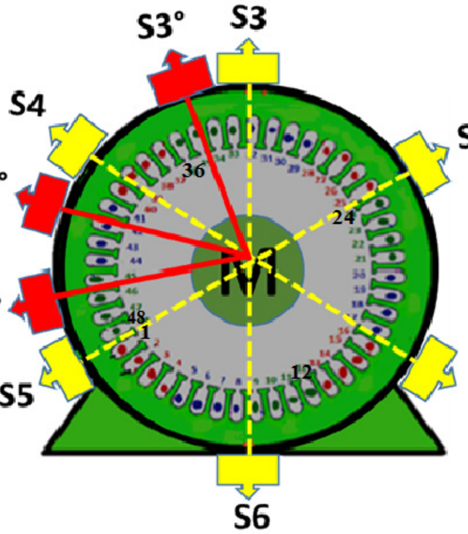

Fig. 1. Illustration of sensors positions around the induction machine

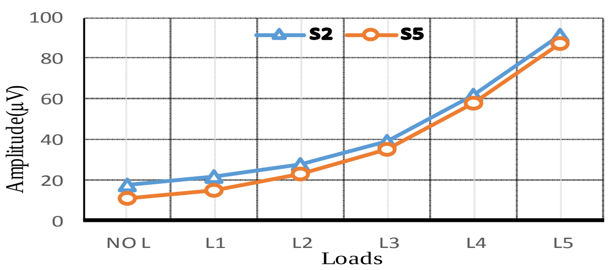

Fig. 2. Harmonic amplitude variation in healthy case of IM

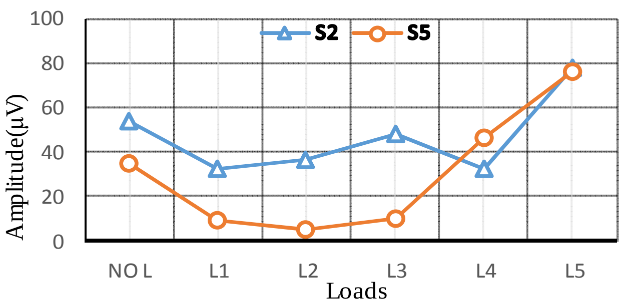

Fig. 3. Harmonic amplitude variation in faulty case of IM with 10A short circuit current

B. Description of fusion proces

Proposed fusion process takes into account, for each position of the sensors two pieces of information:

1. the **difference of variations (DoV)** of the measurements of the harmonic of interest (850 Hz) sensitive at inter-turn short circuit faults, which are output by sensors positioned at 180° from each other as presented in Fig. 1.
2. the **ratio of the amplitudes (RoA)** of these same measurements.

Information **DoV** and **RoA** can be obtained for three positions P1, P2, P3 of the six sensors as illustrated (in yellow) in Fig 1. In the diagnosis problem discusses here, the question Q of interest is the following: "Is there a fault in the machine winding?". The chosen frame of discernment Ω containing the answers to question Q, is then composed of two elements "y" and "n", $\Omega = \{y, n\}$ such that:

- "y" stands for "yes, there is a fault in the winding of the machine";
- "n" indicates that "there is no faults".

For a given position i of a couple of sensors (among the three possible), it remains to build the pieces of information $m_{V,i}$ and $m_{A,i}$ regarding the presence of a fault, which comes respectively from the pieces of evidence DoV and RoA.

For each position, mass function $m_{V,i}$ has been defined as follows:

- If there is at least one difference of evolution between sensor.
- Measurements while the load increases, then $m_{V,i}(\{y\}) = 0.95$ and $m_{V,i}(\Omega) = 0.05$. It represents the fact that there is surely a fault.
- Otherwise (there is no opposite evolutions), we do not know if there is a fault, and there is a small chance that there is no fault, so we define $m_{V,i}$ by $m_{V,i}(\{n\}) = 0.05$ and $m_{V,i}(\Omega) = 0.95$.

The second piece of evidence $m_{A,i}$ regarding the presence of a fault is defined using the following ratio R_i between measurements $mes_{2,i}$ and $mes_{5,i}$ output respectively by sensor S2 and sensor S5 in position i :

$$R_i = \frac{\min(mes_{2,i}, mes_{5,i})}{\max(mes_{2,i}, mes_{5,i})} \tag{4}$$

Values of ratio R_i belong to [0, 1]. When ratio R_i is close to 1, it means that the two measurements are close and then the machine is in a healthy state. When R_i is close to 0, we are almost sure that there is a fault. Between 0 and 1, it is supposed the existence of two thresholds S_1 and S_2 representing a transition. One example of the evolution of the mass function according to the ratio R_i is given in Fig. 4 with $S_1 = 0.45$ and $S_2 = 0.55$. The area between S_1 and S_2 represents a transition area between the two views.

With N the number of possible positions, 2N mass functions $m_{V,i}$ and $m_{A,i}$ are obtained. They correspond to 2N pieces of information regarding the presence of a fault on the machine.

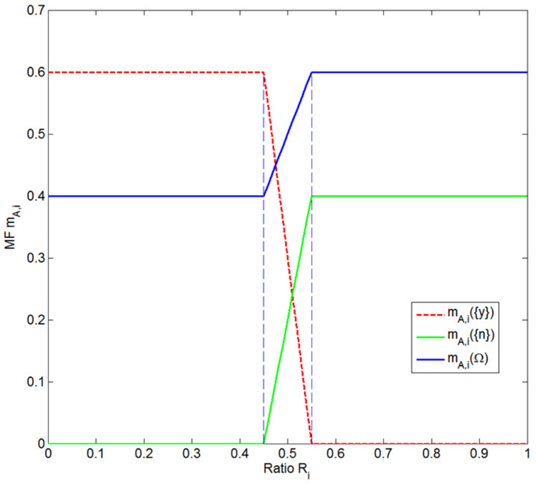

Fig. 4. Definition of mass function (MF) $m_{A,i}$ according to ratio R_i value with two thresholds $S_1 = 0.45$ and $S_2 = 0.55$.

These pieces of information are then combined using CRC (2). The resulting mass function m is given by:

$$m = (\bigcap_{i=1}^{N} m_{V,i}) \bigcap (\bigcap_{i=1}^{N} m_{A,i}) \quad (5)$$

The chosen decision is then the one maximizing the probabilistic transformation $BetP$ of m cf (3).

IV. Experimental results

A. Description of the experimental test bench

The experimental test bench is illustrated in Fig. 5. The amplitude of the harmonic at 850 Hz is analyzed considering a load increase. The considered machine is an IM with 4 poles, 50 Hz, 11 kW, 380/660 V, In = 23 A, $\cos_\varphi = 0.83$, 1450 rpm, 48 stator slots and 32 rotor bars. For the study six external flux sensors are placed on a «belt» fixed around the machine. For simplicity the results concerning the IM are presented as “the harmonic 850 Hz” but actually, the increase of the load leads to a sliding value of this frequency, which decreases with the load increase.

The specific configuration machine allows us to short-circuit any elementary coil x-y (turns placed in two slot x and y) in the stator windings that corresponds to 12.5% of a full phase. The measurements are realized for two load levels and for different positions of short circuit:

- No short-circuit.
- One fault on Phase A (short-circuits on coil 1-13).
- One fault on Phase B (short-circuits on coil 9-21).
- One fault on Phase C (short-circuits on coil 17-29).
- One fault on Phase A’ (short-circuits on coil 25-37).
- One fault on Phase B’ (short-circuits on coil 33-45).
- One fault on Phase C’ (short-circuits on coil 41-5).

The test have be realized with three values of the short circuit current: Icc=5A, Icc=10A, Icc=15A. Here 19 acquisition parameters are globally utilized (six sensors, three Icc and no load healthy case). The severity of the fault depends on the number of shorted turns as well as the short circuit current that is limited by an external resistance.

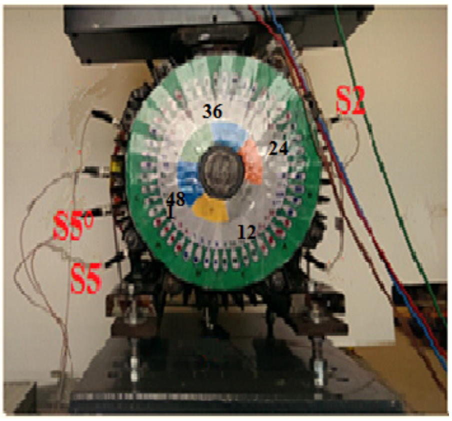

Fig. 5. Experimental IM with six flux sensors placed on a belt.

In the proposed method, six positions of the sensors P1, P2, P3 and P1°, P2°, P3° are considered as shown in Fig.1. In positions P1, P2 and P3 each pair of sensors is located symmetrically relatively to the axis of the machine (spatial shift of 180°). P1 represents the position of the pair of sensors S1- S4, P2 of the sensors S2- S5 and P3 the position of S3- S6. In positions P1°, P2°and P3°, each pair of sensors is not symmetrically placed around of the machine frame. Here, for P1° corresponding to the pair S1- S4° the sensors are placed at 205° spatial shift around IM, for P2° corresponding to S2 - S5° at 205° and for P3° corresponding to S3 - S6° at 165° from each other.

B. Calculation examples

Table II shows the measurements obtained for P1, P2, P3 positions on a machine with a 5A short circuit current measured in the short-circuit coil 17-29 for sensors placed at 180° around the IM.

TABLE II. Example of Measurements Obtained from Three Positions (5A short circuit current)

Load (W)	**Position P1**		**Position P2**		**Position P3**	
	S 1 (µV)	**S 4** (µV)	**S 2** (µV)	**S 5** (µV)	**S 3** (µV)	**S6** (µV)
0	5.05	20.3	27.8	4.03	4.72	15.8
L1	5.95	26.4	39.8	3.08	8.6	21.5
L2	9.03	28.4	45.2	3.55	7.09	34.6

Differences of variations for each sensor at position P2 (sensors S2-S5) are exposed in Table III.

TABLE III. Differences of Variations Obtained From Sensors S2 and S5 Using the Induction Machine for Position P2

Load (W)	**S 2** (µV)	**S2** Variation	**S 5** (µV)	**S 5** Variation	**Same variation?**
0	27.8		4.03		
L1	**39.8**	**12**	**3.08**	**-0.95**	**no**
L2	45.2	5.4	3.55	0.47	yes

Table IV summarizes the number of different variations observed for all positions.

TABLE IV. NUMBER OF DIFFERENT VARIATIONS DETECTED FOR EACH POSITION OF THE SENSORS

	Position P1	**Position P2**	**Position P3**
Number of different variation	0	1	1

Consequently, the obtained mass functions $m_{V,i}$, for each position i, $i \in \{1,2,3\}$ are given in Table V.

TABLE V. MFS, $m_{V,i}$ OBTAINED FROM THE MEASUREMENTS EXPOSED

Position P1	**Position P2**	**Position P3**
$m_{V,1}(\{n\}) = 0.05$ $m_{V,1}(\Omega) = 0.95$	$m_{V,2}(\{y\}) = 0.95$ $m_{V,2}(\Omega) = 0.05$	$m_{V,3}(\{y\}) = 0.95$ $m_{V,3}(\Omega) = 0.05$

As a difference of evolution was detected in position P2 and position P3 MF, $m_{V,2}$ indicates the presence of a fault, whereas it is not the case for position P1.

Result after the combination using (2) of these 3 MFs is given by:

$$\begin{cases} m_V(\{y\}) = 0.947 \\ m_V(\{n\}) = 0.001 \\ m_V(\Omega) = 0.002 \\ m_V(\varnothing) = 0.050 \end{cases}$$

We consider now the ratio of the amplitudes (**RoA**) as a second piece of information regarding the presence of a fault. Ratios obtained in position P2 are presented in Table VI. Only the smallest is conserved for R_2.

TABLE VI. RATIOS ROA OBTAINED FROM THE MEASUREMENTS OF TABLE III IN POSITION 2.

Load (W)	**S 2** (µV)	**S 5** (µV)	**Ratio**	R_2
0	27.8	4.03	0.145	0.078
L1	39.8	3.08	0.078	
L2	45.2	3.55	0.079	

Ratios R_1 and R_3 are similarly computed for positions P1 and P3. Associated MFs are then computed (cf Section III, Fig. 4). Results are summarized in Table VII.

TABLE VII. : MFS, $m_{A,i}$ OBTAINED WITH THE EXAMPLE MEASUREMENT OF TABLE III.

Position P1 $(R_1 = 0.226)$	**Position P2** $(R_2 = 0.078)$	**Position P3** $(R_3 = 0.205)$
$m_{A,1}(\{y\}) = 0.6$ $m_{A,1}(\Omega) = 0.4$	$m_{A,2}(\{y\}) = 0.6$ $m_{A,2}(\Omega) = 0.4$	$m_{A,3}(\{y\}) = 0.6$ $m_{A,3}(\Omega) = 0.4$

The combination of these MFs yields to

$$\begin{cases} m_A(\{y\}) = 0.936 \\ m_A(\{n\}) = 0 \\ m_A(\Omega) = 0.064 \\ m_A(\varnothing) = 0 \end{cases}$$

Combining m_A and m_V gives a MF defined by:

$$\begin{cases} m(\{y\}) = 0.949 \\ m(\{n\}) = 0 \\ m(\Omega) = 0.001 \\ m(\varnothing) = 0.050 \end{cases}$$

At last, the pignistic transformation of m being (3)

$$\begin{cases} BetP(\{y\}) = 0.999 \\ BetP(\{n\}) = 0.001 \end{cases}$$

It follows a decision in favor of $\{y\}$.

C. *Global Results*

The comparative analysis measures the influence of the sensors position around the machine in detection of the inter turn short circuits in electrical machines. It considers the cases when the sensors are placed exactly at 180° around the IM or shifted using three types of loads and three types of short circuit current corresponding to different severity faults.

The results obtained by these cases are studied, in the first one using only information regarding the difference of variation (**DoV**), the second one using only information regarding the amplitude ratio (**RoA**) and in the last one using all the available information.

TABLE VIII. PERCENT OF CORRECT DECISION FOR ASYNCHRONOUS MACHINE WITH SENSORS POSITIONED AT 180°. THE NUMBER IN BRACKETS INDICATES THE NUMBER OF NO DETECTION. THE BEST RESULT IS HIGHLIGHTED IN BOLD FONT

	No fault (1)	fault 5A (6)	fault 10A (6)	fault 15A (6)	Overall Results (19)
Fusion of only information regarding the difference of variation in each position $\left(\bigcap_{i=1}^{3} m_{V,i}\right)$	**100 (0)**	**100 (0)**	83.33 (1)	16.66 (5)	68.42 (6)
Fusion of only information regarding the amplitude ratio in each position $\left(\bigcap_{i=1}^{3} m_{A,i}\right)$	0 (1)	**100 (0)**	**100 (0)**	66.66 (2)	84.21 (3)
Fusion of all the mass functions $\left(\bigcap_{i=1}^{3} m_{V,i}\right) \cap \left(\bigcap_{i=1}^{3} m_{A,i}\right)$	**100 (0)**	**100 (0)**	83.33 (1)	**83.33 (1)**	**89.47 (2)**

For the first case (sensors at 180^0), the results are depicted in Table VIII; the best result is obtained by combining all the information. The overall results allow us to achieve the best probability of fault detection. For exactly positioning of the sensors it is obtained by this method 89.47% correctly detection cases against to 84.21 % with information regarding only the amplitude ratio and 68.42% with information regarding only the difference of variation. For the second case, (sensors shifted from180^0) the results are depicted in Table IX; the best result is obtained by combining all the information. Here, 89.47% correctly detection is obtained too against 78.95% with information regarding only the amplitude ratio and 73.68% with information regarding only the difference of variation.

TABLE IX. PERCENT OF CORRECT DECISION FOR ASYNCHRONOUS MACHINE WITH SHIFTED SENSORS. THE NUMBER IN BRACKETS INDICATES THE NUMBER OF NO DETECTION. THE BEST RESULT IS HIGHLIGHTED IN BOLD FONT

	No fault	fault 5A	fault 10A	fault 15A	Overall Results
Fusion of only information regarding the difference of variation in each position $(\bigcap_{i=1}^{3} m_{V,i})$	**100 (0)**	**100 (0)**	**100 (0)**	16.66 (5)	73.68 (5)
Fusion of only information regarding the amplitude ratio in each position $(\bigcap_{i=1}^{3} m_{A,i})$	0 (1)	83.33 (1)	83.33 (1)	**83.33 (1)**	78.95 (4)
Fusion of all the mass functions $(\bigcap_{i=1}^{3} m_{V,i}) \cap (\bigcap_{i=1}^{3} m_{A,i})$	**100 (0)**	**100 (0)**	83.33 (1)	**83.33 (1)**	**89.47 (2)**

V. COUNCLUSON

In this paper a diagnosis method developed for detection of the inter-turn short circuit in the stator winding in induction motor is presented. It is based on a fusion technique with the belief function theory. This method is interesting because it is non-invasive, inexpensive and easy to implement. Furthermore, it does not require the knowledge of the machine healthy state. It uses the load variation to perform the fault detection and two specific pieces information, namely: the difference of variation "DoV" and the ratio of the amplitudes "RoA", to detect the fault probability. The influence of the precision in the sensor positioning around the machine and the influence of the faulty severity are considered in the study to analyze the method reliability. It can be observed that this method allows a low shifted in the sensors positions, which do not modify the diagnosis results. However, the information provided by the sensors are dependent on the level of short circuit current and the load of the machine, so the sensors must be adapted to faulty level to obtain a high detection percentage level and reliability.

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