Information fusion with Correlation Coefficient for detecting inter-turn short circuit faults in asynchronous machines

M. Irhoumah, R. Pusca, E. Lefèvre, D. Mercier, R. Romary

***Abstract* — This paper presents a new method giving high efficiency for detecting an inter-turn short-circuit fault in the stator winding of asynchronous machines. For evaluation of the machine state and final decision, the monitoring of the magnetic field variation in the vicinity of an electrical machine is used. The proposed approach is based on the fusion of information extracted from signals delivered by flux sensors placed in different positions around the machine and the calculation of Pearson correlation coefficient. This coefficient allows one to quantify the linear relationship between the signals delivered by two sensors S1 and S2 placed at 180° around the machine in several positions. The proposed approach is non-invasive and relies on the calculation of a correlation coefficient derived from measurements of the external magnetic leakage field for different load working cases. The ability of proposed coefficient to provide useful information about faults is investigated in the paper.**

***Index Terms* — Asynchronous machines, correlation coefficient, external magnetic field, fault diagnostic, information fusion, inter-turn short circuit.**

I. INTRODUCTION

THE production losses due to a stop relating to an electrical machine failure are more significant than that caused by the actual machine efficiency. The failure of the machines, therefore, reduces the production rate and increases the costs of production and maintenance. So these machines need to be monitored during the production process to improve the reliability of machine operation and to reduce the downtime.

Electrical machines are subject to mechanical faults common to most rotating machines [1], such as eccentricity Faults [2], mechanical imbalance [3], bearing faults [4], or resonance [5]. But electrical machines also have their own specific problems like the defect of the stator winding or rotor broken bars, which will produce magnetic imbalance.

For this reason, monitoring devices based on information provided by magnetic flux sensors can be effectively used to detect internal imbalances. Classical methods currently used for the diagnosis of electrical machines are based on the measurement of noise [6], current [7], vibration [8], torque and temperature [9]. These methods give many significant results but still encounter some issue. It is, for example, necessary to detect these faults using the same standard sensors like those used for other purposes, such as current and voltage sensors. On the other hand, it is necessary to know the healthy state of the machine. The efficiency of these methods, known as invasive methods, have already been proven in industry. However, their use is usually restricted to specific applications (power plants, security installations, systems with significant economic interest) because they often work in combination with other systems monitoring. Thus, their costs, or the need to use specialized staff, limit their generalization. Diagnosis methods based on the measurement and analysis of magnetic flux outside of electrical machines have been developed since the 70' [10] and they are still the subject of research as related in [11]. On the basis of an evaluation from numerous tests, the external leakage flux can be considered as one of the most practical signal containing information necessary for the detection of faults, such as eccentricities [12], rotor broken bars [13] or short-circuit between turns in the stator winding [14][15]. These methods can be associated with a variety of analytical techniques and can be promising approaches for industrial diagnosis [16]. Some examples include the fusion of information with belief functions [17], or correlation coefficient methods to detect stator faults [18].

In this work, the Pearson correlation coefficient combined with fusion methods is proposed to improve the detection of short-circuit faults between turns of the AM stator winding. It is based on the analysis of the external magnetic field which loses its symmetry in faulty case. The main advantage is that the external magnetic field is more sensitive than current to detect a magnetic dissymmetry.

The third section of this paper introduces the proposed diagnostic method and gives the definition of the Pearson correlation coefficient. The fourth section presents the calculating method of the correlation coefficients and their fusion procedure using experimental results. Conclusion and

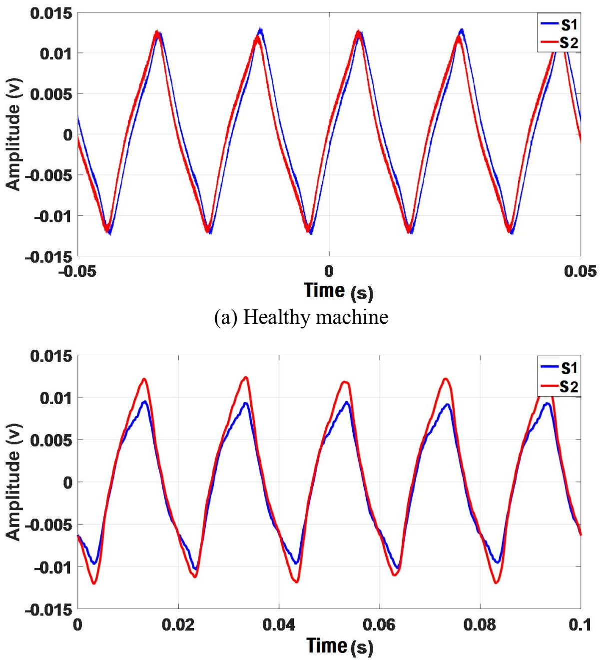
M. Irhoumah, R. Pusca, R. Romary members of Laboratory of Electrotechnical and Environmental Systems (LSEE) specializes in electrical engineering, University Artois, EA 4025 LSEE, F-62400, Bethune, France, (e-mail: miftahaldwiab_irhoumah@ens.univ-artois.fr).

E. Lefevre, D. Mercier members of Laboratory of Computer Engineering and Automation (LGI2A) University Artois, EA 3926 LGI2A, F-62400, Bethune, France specializes in Decision support for sustainable logistics and mobility david.mercier@univ-artois.fr.

suggested future works are presented in the last section.

II. DIAGNOSTIC METHOD

Some diagnostic methods have been proposed to detect stator short circuits that rely on the fact that stator asymmetry causes an increase or a decrease in the amplitude of sensitive harmonics generated by a fault [19]. As a consequence, the amplitude of specific harmonics of the air-gap flux density, and thus of the external magnetic field, may be considered useful to obtain reliable results. The asymmetry leads to a difference between the electromagnetic forces (fem) delivered by two external flux sensors S1 and S2 placed at 180° around the electric machine as shown in Fig.1 and so to a dissymmetry between the corresponding harmonics.



(a) Healthy machine

(b) Faulty machine

Fig. 1. Signals delivered by two coil sensors S1 and S2 placed at 180^0 around of MA machine of 11 KW: a) electromagnetic force measured for healthy machine, b) electromagnetic force measured for the faulty machine.

The amplitudes of the considered harmonics sensitive to the stator inter-turn short-circuit fault are used as inputs to calculate the Pearson correlation coefficient "r". These different amplitudes are noted $mes_{1,i}(k)$ and $mes_{2,i}(k)$ for different load conditions k and different positions i. Thus, the correlation coefficient is expressed by:

$$r_i = \frac{\sum_{k=1}^{n} mes_{1,i}(k).mes_{2,i}(k) - \frac{\sum_{k=1}^{n} mes_{1,i}(k) \sum_{k=1}^{n} mes_{2,i}(k)}{n}}{\sqrt{\left(\sum_{k=1}^{n} mes_{1,i}(k)^2 - \frac{\left(\sum_{k=1}^{n} mes_{1,i}(k)\right)^2}{n}\right)\left(\sum_{k=1}^{n} mes_{2,i}(k)^2 - \frac{\left(\sum_{k=1}^{n} mes_{2,i}(k)\right)^2}{n}\right)}} \quad (1)$$

The following interpretation of the correlation coefficient is applied:

- If r_i is close to 0, it means that the amplitudes of the harmonics do not vary in a similar way and therefore there is no linear relationship between these variables. This indicates the presence of a fault in the stator of the machine.
- If r_i is close to -1, this indicates a strong negative relationship between the variables. The relationship is negative because when one variable increases, the other variable decreases and as described in [13], when the amplitudes of the field harmonics vary in opposite directions in case of load variation, there is a defect in the stator of the machine.
- On the contrary, when r_i is close to 1, it means that the two measurements evolve in the same way according to the variations of the load. This means that the machine may be in good condition, but we do not know for sure because we are not yet aware of other positions.

With N positions, we obtain N correlation coefficients. Each coefficient constitutes a piece of information regarding the presence of a fault. Fusion technique using belief functions [18] is then used as a frame to represent and combine information to make a final decision concerning the question of the presence of a fault. To use the belief function theory, the first step is to define a frame of discernment Ω which is composed by the true value taken by a variable of interest x. In our case, this frame of discernment is composed by two elements "y" and "n", Ω = {y, n}, such that "y" represents the fact that "there is a fault" and "n" indicates "no fault". The objective is then to define a mass function $m_{r,i}$ as an information regarding the presence of a fault provided by each correlation coefficient r_i obtained at the position i. An example of the evolution of the mass function according to the value of the coefficient r_i is given in Fig. 2. Considering N number of possible positions of the sensors, we obtain N mass functions corresponding to N information about the presence of a fault on the machine. This information is then combined using the following equation:

$$m_r = \left(\bigcap_{i=1}^{N} m_{r,i}(A) \right) \quad \forall A \subseteq \Omega \quad (2)$$

In case the of two mass functions $m_{r,1}$ and $m_{r,2}$ provided respectively by r_1 and r_2, this equation is written:

$$m_r(A) = \sum_{B \cap C = A} m_{r,1}(B).m_{r,2}(C) \quad \forall A \subseteq \Omega \quad (3)$$

This rule being associative and commutative, the order considered for combined sources does not affect the combination result.

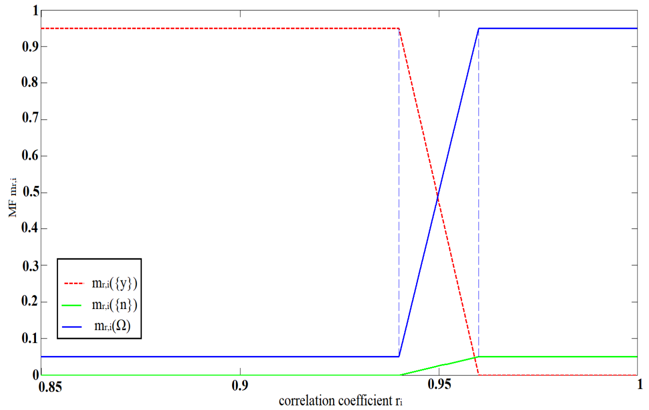


Fig. 2. Evolution of the mass function as a function of the value of the correlation coefficient r_i.

One way of making a decision once the available information about the true value taken by x is represented by a single mass, is to transform that mass m into the probability measure $BetP$ defined by:

$$BetP(\{x\}) = \sum_{x \in A, A \subseteq \Omega} \frac{m(A)}{|A|(1-m(\phi))} \quad \forall x \in \Omega \qquad (4)$$

where |A| is the number of elements included in “A”, (its cardinality). The proposed procedure method is realized in several steps illustrated in Fig.3. The first step corresponds to measurement of external magnetic field (fem) variation in different positions (P1, P2,… Pn) around the machine by the sensors S1 and S2. In the second step the amplitudes of the fem harmonics (only the harmonics sensitive or the fault is extracted from the spectrum) are considered to calculate the Pearson correlation coefficient “r_1, r_2, ….r_n ”. In the third step the fusion of obtained correlation coefficients is realized and in the last one the decision is obtained by transforming the mass function into the probability measure.

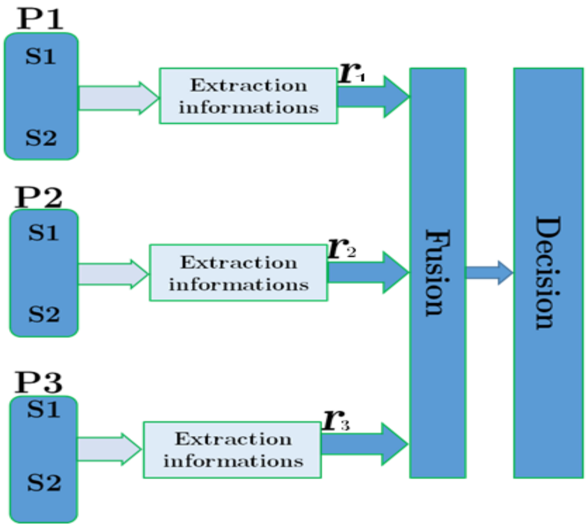


Fig. 3. Representation of the proposer procedure method for transforming the fem signal measured by the sensors S1 and S2 in probability information about presence of a short-circuit fault in the machine.

III. Experimental results

In experimental tests, the results are obtained from an AM characterized by 4-poles (p=2), 50Hz, 11kW, 380/660V, 22.3/13A, 1450 r/min, 48 stator slots (N^s=48) and 32 rotor bars (N^r=32) which allow us to simulate a damaged coil (short-circuited turns) in each elementary coil (turns in a slot). A rheostat is used to limit the value of short-circuit current in the stator windings in order to protect the windings.

For this machine, the sensitive harmonics are given by [17]:

$$f = f_s(1 \pm (1-s)N^r/p) \qquad (5)$$

At f_s=50Hz supply frequency, the sensitive harmonics are at 750Hz and 850Hz when s=0. These frequencies decrease when the load increases. The measurement of the external magnetic field is carried out with 6 sensors in three positions; each pair of sensors are shifted by 180° as shown in Fig.4.

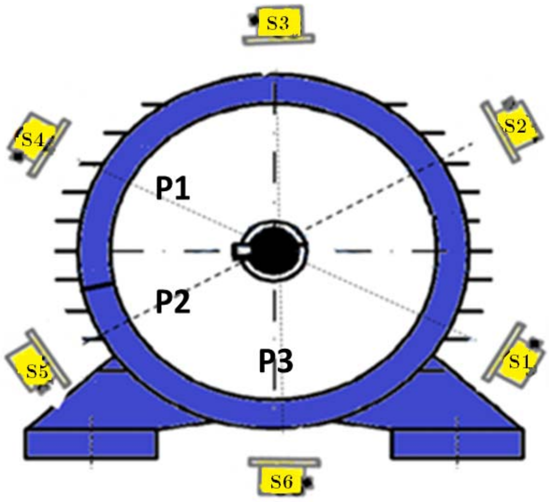


Fig. 4. Position of sensors placed around of the asynchronous machine.

The configurations studied for this machine are the following:

- Without short circuit,
- Two faults on phase A: p1(1-2) and p2(9-10)
- Two faults on phase B: p3(17-18) and p4(25-26)
- Two faults on phase C: p5(33-34) and p6(41-42)

The values of the currents measured in each case of short circuit are:

- Icc = 5A,
- Icc = 10A,
- Icc = 15A.

This configurations lead to discriminate 19 cases (18 with faults and 1 healthy). The measurements obtained by the sensors for the three positions are summarized in Table I in the case of healthy machine and in Table II in case of faulty machine (fault in phase A, Icc=15A). Here the magnitude of the harmonic at 850Hz is given.

TABLE I
EXAMPLE OF MEASUREMENTS OBTAINED FROM THREE POSITIONS FOR HEALTHY MACHINE

	(P1)		(P2)		(P3)	
loads	S1(μV)	S4(μV)	S2(μV)	S5(μV)	S3(μV)	S6(μV)
no load	11	23	18	11	20	11
load 1	14	24	22	15	26	12
load 2	19	30	28	23	36	16
load 3	27	42	39	35	54	24
load 4	43	69	62	58	89	41
load 5	64	105	91	87	132	61

TABLE II
EXAMPLE OF MEASUREMENTS OBTAINED FROM THREE POSITIONS FOR FAULTY MACHINE

	(P1)		(P2)		(P3)	
loads	S1 (μV)	S4(μV)	S2(μV)	S5 (μV)	S3(μV)	S6(μV)
no load	45.6	202.7	219.2	131.8	64.3	267.4
load 1	45	148.5	194.9	109.5	58.9	212.2
load 2	30.1	44.1	96	38.4	47.4	66.5
load 3	41.4	46.8	47.7	43.2	59.6	52.4
load 4	36	41.3	15.1	16.5	67.7	83.7
load 5	59.1	67.8	114.5	66	108.2	169

Using measured values as inputs in (1), it is obtained the values of correlation coefficients "r_i" for three positions which are presented in Table III.

TABLE III
CORRELATION COEFFICIENTS OBTAINED FROM THREE POSITIONS IN FAULTY MACHINE (HEALTHY ONLY FOR ONE CASE)

		P1	P2	P3
	No fault	0.9969	0.9964	0.9998
p1 (1-2)	5A	0.9787	0.923	0.9838
	10A	0.9104	0.5381	0.7955
	15A	**0.7336**	**0.7356**	**0.999**
p2 (9-10)	5A	0.9909	0.9964	0.6898
	10A	0.9256	0.8436	0.9854
	15A	0.8695	0.9973	0.5938
p3 (17-18)	5A	0.6566	0.9248	0.9978
	10A	0.5235	0.9425	0.7203
	15A	0.7193	0.9901	0.7258
p4 (25-26)	5A	-0.3216	0.9481	0.9326
	10A	0.8169	0.5203	0.7485
	15A	0.831	0.9667	0.7416
p5 (33-34)	5A	0.7537	0.9532	0.9988
	10A	0.967	-0.3941	0.9549
	15A	0.9696	-0.4057	0.9685
P6 (41-42)	5A	0.98	0.9731	0.9305
	10A	0.9801	0.6573	0.9495
	15A	0.9589	0.738	0.6433

1) *Example of calculation of belief functions, fusion and probability of fault*

In this example, we take the case of the faulty machine where the short circuit current measured in the phase 1 between the windings 1-2 is 15A. The mass functions $m_{r,i}$ is obtained using Fig. 2. In this case, with r_1 = 0.7336, we obtain the following mass function: $m_{r,1}(\{y\})=0.95$ and $m_{r,1}(\Omega)=0.05$ where $m_{r,1}(\Omega)$ represents the information "I do not know if there is a fault". The same operation is realized for r_2 and r_3. All mass functions obtained, in this example, are presented in Table IV. In this table, $m_{r,i}(\Phi)$ represents the conflict.

TABLE IV
MASS FUNCTIONS $m_{r,i}$ OBTAINED FROM THE CORRELATION COEFFICIENT PRESENTED IN TABLE III.

In case of the Faulty machine p1(1-2) 15A		
Position $P1$ (r_1 = 0.7336)	Position $P2$ (r_2 = 0.7356)	Position $P3$ (r_3 = 0.999)
$m_{r,1}(\{y\})=0.95$	$m_{r,2}(\{y\})=0.95$	$m_{r,3}(\{y\})=0$
$m_{r,1}(\{n\})=0$	$m_{r,2}(\{n\})=0$	$m_{r,3}(\{n\})=0.05$
$m_{r,1}(\Omega)=0.05$	$m_{r,2}(\Omega)=0.05$	$m_{r,3}(\Omega)=0.95$
$m_{r,1}(\Phi)=0$	$m_{r,2}(\Phi)=0$	$m_{r,3}(\Phi)=0$

To obtain, an unique mass function, we use the combination rule defined by (2) and (3). Numerical application of this combination rule is presented in table V.

TABLE V
NUMERICAL APPLICATION EXAMPLE OF COMBINATION OF THE MASS FUNCTIONS $m_{r,i}$

STEP1

In case of the Faulty machine p1(1-2) 15A		
(r_1 = 0.7336)	(r_2 = 0.7356)	result obtained by (3)
$m_{r,1}(\{y\})=0.95$	$m_{r,2}(\{y\})=0.95$	$y \cap y = y$ 0.95x0.95=0.9025
$m_{r,1}(\{y\})=0.95$	$m_{r,2}(\{\Omega\})=0.05$	$y \cap \Omega = y$ 0.95x0.05=0.0475
$m_{r,1}(\{\Omega\})=0.05$	$m_{r,2}(\{y\})=0.95$	$\Omega \cap y = y$ *0.05x0.95=0.0475*
$m_{r,1}(\{\Omega\})=0.05$	$m_{r,2}(\{\Omega\})=0.05$	$\Omega \cap \Omega = \Omega$ 0.05x0.05=0.0025
$\sum_{B\cap C=A} m_{r,1}(B).m_{r,2}(C)$		$m'_{r,12}(\{y\})=0.9975$ $m'_{r,12}(\{\Omega\})=0.0025$

STEP2

In case of the Faulty machine p1(1-2) 15A		
$r_{1,2}$	r_3	result obtained by (3)
$m'_{r,12}(\{y\})=0.9975$	$m_{r,3}(\{n\})=0.05$	$y \cap n = \Phi$ 0.9975x0.05=0.0499
$m'_{r,12}(\{y\})=0.9975$	$m_{r,3}(\{\Omega\})=0.95$	$y \cap \Omega = y$ 0.9975x0.95=0.9476
$m'_{r,12}(\{\Omega\})=0.0025$	$m_{r,3}(\{n\})=0.05$	$\Omega \cap n = n$ 0.0025x0.05=0.0001
$m'_{r,12}(\{\Omega\})=0.0025$	$m_{r,3}(\{\Omega\})=0.95$	$\Omega \cap \Omega = \Omega$ 0.0025x0.95=0.0024
$m_r(A) = \sum_{B\cap C=A} m'_{r,12}(B).m_{r,3}(C)$		$m_r(\{y\})=0.9476$ $m_r(\{n\})=0.0001$ $m_r(\{\Phi\})=0.0499$ $m_r(\{\Omega\})=0.0024$

The final mass function is for "yes" $m_r(\{y\})$ =0.9476, for "no" $m_r(\{n\})$ = 0.0001, for "I do not know" m_r (Ω) = 0.0024 and for conflict mass m_r (Φ) = 0.0499.

One way of making a decision once the available information about the true value taken by x is represented by a single mass, is to transform that mass *m* into the probability measure *BetP* defined by (4). In case of the faulty machine (p1(1-2)   15A) eq. (4) can be written:

$$BetP(\{y\}) = \frac{m_r(\{y\})}{|1|(1-m_r(\phi))} + \frac{m_r(\{\Omega\})}{|2|(1-m_r(\phi))}$$

$$BetP(\{y\}) = \frac{0{,}9476}{|1|(1-0{,}0499)} + \frac{0{,}0024}{|2|(1-0{,}0499)} = 0{,}9986$$

and

$$BetP(\{n\}) = \frac{m_r(\{n\})}{|1|(1-m_r(\phi))} + \frac{m_r(\{\Omega\})}{|2|(1-m_r(\phi))}$$

$$BetP(\{n\}) = \frac{0{,}0001}{|1|(1-0{,}0499)} + \frac{0{,}0024}{|2|(1-0{,}0499)} = 0{,}0014$$

So we get *Betp* ({y}) = 0.9986 probability for "yes" and Betp ({*n*}) = 0.0014 for "no". Considering obtained probability it follows a decision in favor of the hypothesis {y} which means that there is a fault on the considered machine. The same calculus is applied for each case of 19 cases presented in Table III

2) Results obtained for global tests

Let us analyze influence of the multiplying the number of positions around the machine on the efficiency of fault detection.

The measurement is relative to one healthy case plus 18 faulty cases, corresponding to faults at different positions of the stator. One case takes into account several load level, and signals picked up by two sensors placed at three positions as depicted in Fig. 4. The results for this machine are presented in table VI.

TABLE VI
PERCENT OF CORRECT DECISIONS FOR EACH SERIES WITH ASYNCHRONOUS MACHINE

P1	P2	P2	Fusion of the three positions
68.42 (6)	73.68 (5)	68.42 (6)	100 (0)

Here, the results are given as percentage of correct detections.

To analyze the effect of the number of positions on the effectiveness of fault detection, the following values were taken into account:

- With position P1, the method can detect percentage defects equal to 68.42%.
- With position P2, the method can detect percentage defects equal to 73.68%.
- With position P3, the method can detect percentage defects equal to 68.42%.

In presented test the fusion of three position (P1, P2 and P3), means that the measurements were realized with sensors in the three positions at the same time. In this case the method has detected percentage defects equal to 100% as shown in Fig.5.

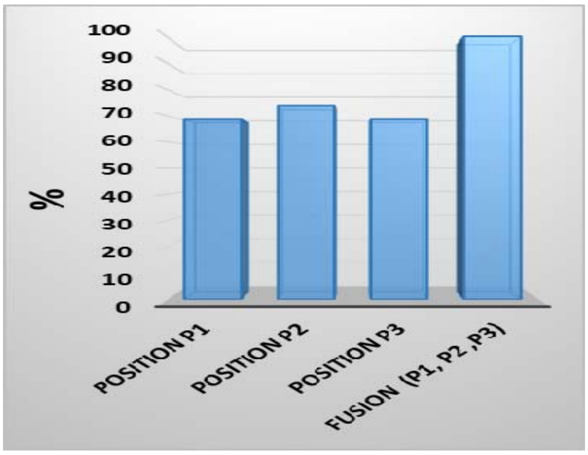


Fig. 5. Effect of the number of positions on the effectiveness of fault detection.

From this result, we remarked that the detection percentage can be increased by multiplying the number of positions around the machine.

IV. CONCLUSION

The work presented in this paper shows a new method to detect the short-circuit between the stator winding of asynchronous machines. This method is based on calculation of Pearson correlation coefficient and fusion of obtained coefficients with belief functions to analyze the external magnetic field variation. Obtained results show the increase of detection percentage by multiplying the number of measurement positions around the machine to highlight the stator field asymmetry generated by the fault. The method has the advantage of being fully non-invasive and it does not require the knowledge the healthy state. As only load variations are required, the method is easy to use in an industrial application because the system just need to follow the operating condition of the machine and to peak up data from the external field at predefined times. In further works this analysis method will be tested for other type of motor and others faults in order to define its limit.

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AUTHORS' INFORMATION

Miftah Irhoumah received the Master degree of Technology in Industrial Automation from the Faculty of Engineering in the University of Tripoli (Lybia) in 2008. He has technical experience in the electricity laboratories and automatic control. He is actually pursuing PhD studies in the Laboratory of Electrotechnical and Environmental Systems (LSEE), at Artois University in France in the field of diagnosis of electrical machines.

Remus Pusca was born in Medias, Romania, in 1972. He received in 1995 the electrical engineering degree from Technical University of Cluj-Napoca, Romania. He obtained in 2002 Ph.D. degree in electrical engineering, from the University of Franche-Comté, France.In 2003, he joined the Laboratory of Electrical Systems and Environment (LSEE), Artois University, Béthune, France, as an Associate Professor and Researcher. His research interest is control of electrical systems and diagnosis of electrical machines.

Eric Lefevre received, in 2001, the Ph.D. in physics from National Institute of Applied Sciences (INSA) of Rouen, France. He joined Univeristy of Artois in 2002, as associate professor. He obtained the French Research Habilitation (HDR) from Uniservity of Artois in 2012 and, as of 2013, he is full professor. His research interests include uncertainty modeling and information fusion with belief functions.

David Mercier received the PhD from the University of Technology of Compiègne (UTC), France, in 2006. Since September 2008, he is an Associate Professor at the University of Artois, France, after having been an Assistant Professor (French ATER) from September 2007 to August 2008. Since September 2012, he is an elected member of the executive board of the Belief Functions and Applications Society. He obtained his French Research Habilitation (HDR) from the University of Artois in 2015. His research interests include information fusion and reasoning with uncertainty in particular with belief functions.

Raphaël Romary (M'10) received the Ph.D. from Lille University, Lille, France, in 1995 and the D. SC degree from Artois University, Béthune, France, in 2007. He is currently a Full Professor in Artois University and a Researcher at the Laboratory of Electrical Systems and Environment (LSEE). His research interest concerns the analytical modeling of electrical machines with applications to noise and vibration, losses, electromagnetic emissions, diagnosis.