Robust Diagnostic Based on High Frequency Resonance Measurements

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ABSTRACT

The stator insulation breakdown is a major cause of AC machine failures. Ground insulation defaults are easily detected by classical systems based on leakage current measurements, however the turn-to-turn insulation degradations are more difficult to detect. For large machines, on-line methods, based on partial discharge detection and analysis, give good results but they cannot be used for low-voltage machines fed by adjustable speed drives (ASD). Previously, it has been shown by some of the authors that it was possible to estimate the aging of an AC machine winding thanks to HF measurements of current or magnetic field. In this paper, it is proposed to exploit conjointly all these different estimations to obtain a more robust and reliable diagnostic. The merging of the different estimations being realized through the belief functions framework, this approach is tested on real measurements.

Index Terms — **AC machines, life estimation, machine windings, rotating machine insulation, power system monitoring, merging information, Dempster-Shafer theory of belief functions.**

1. INTRODUCTION

STATOR insulation failures involve about one third of the total number of AC machines outages in industrial environment [1]. The stator insulation failure mechanism is now well-known; it often begins with a local turn-to-turn breakdown, which creates a supplementary thermal stress and an extension of the damage that may reach the ground wall insulation, if the power supply is not switched-off [2]. For many industrial applications, motor failures cause unforeseen production stoppages, which are very expensive. To avoid such problems, preventive maintenance is required for crucial machines. Several classical methods can be used for ground insulation testing [1], but it is more difficult to evaluate the quality of the turn insulation which is the only way to detect the very beginning of an insulation problem, particularly for inverter fed machines. Until now, very few methods are available. It is possible to perform an impulse testing on an off-line machine [3], or to follow the PD activity on a high voltage working machine [4, 5] or with off-line PD testing systems [6].

This paper presents an on-line monitoring system able to give information on the aging of the turn insulation of AC machine. The system is based on the indirect measurement of the turn-to-turn capacitance followed by an information fusion method. Results of the measurements made on a typical magnet wire [7], which shows that the specimen capacitance increases with the insulation aging. Correlations between the variations of this capacitance, the breakdown voltage and the cumulative probability of failure are established. The first part of this document describes how to observe the aging of an ac machine winding and the on-line monitoring system, based on high frequency measurements on the windings of a machine in service. The second part presents the decision-making process regarding the aging of the machine. This process is based on the fusion of information provided by HF measurements of current and magnetic fields. When a measure is precise and certain, no other measure is necessary. However, such a measure is rarely obtained in real world applications. Information fusion consists then in merging, or exploiting conjointly, several imperfect sources of information to make proper decision. Various frameworks can be used to model the fusion, e.g., probability theory, possibility theory, belief functions [8, 9]. In the second part of the paper, the different measurements of the aging of an AC machine winding are combined in the latter frame. This method is tested on data resulting from measurements on a 4 kW inverter fed machine and allows us to obtain a more robust and reliable diagnostic.

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2. AGING OF AN AC MACHINE AND MONITORING SYSTEM

2.1 INFLUENCE OF AGING ON TURN-TO-TURN CAPACITANCE

Thermal accelerated aging was performed in a previous study on specimens made with a polyesterimide (THEIC) magnet wire according to the IEC 60851-5 standard [7, 10]. The thermal accelerated aging of magnet wire shows the correlation between the specimen capacitance variations and the quality of the insulation between wires. It proves that the capacitance variations can be used as an indicator of the winding turn insulation aging. Figure 1 and Figure 2 presents respectively the mean value and breakdown voltage and capacitance of identical specimen versus aging time for a thermal stress of 250°C. A model developed in [7] shows that such capacitance variations yields significant variations of resonance frequencies in machine windings. In a real case, the turn-to-turn capacitance cannot be measured on a machine. However it is possible to measure the capacitance corresponding to the equivalent RLC parallel circuit that represents the winding first resonance. For a frequency range up to 10 MHz, a simple parallel RLC equivalent circuit represents roughly the machine winding frequency behavior [11]. The global capacitance Cg, defined for the RLC parallel equivalent circuit, includes the turn-to-turn capacitance Ci and the turn to core capacitance Cm :

$$Cg = f(Ci, Cm) \quad (1)$$

The numerical value of Ci is much higher than Cm; consequently, the global capacitance Cg is then much more influenced by turn-to-turn capacitance Ci. The variation of Cg corresponds approximately to the variation of Ci and the variation of the first parallel resonance can be considered as an indirect effect of the degradation of the turn insulation.

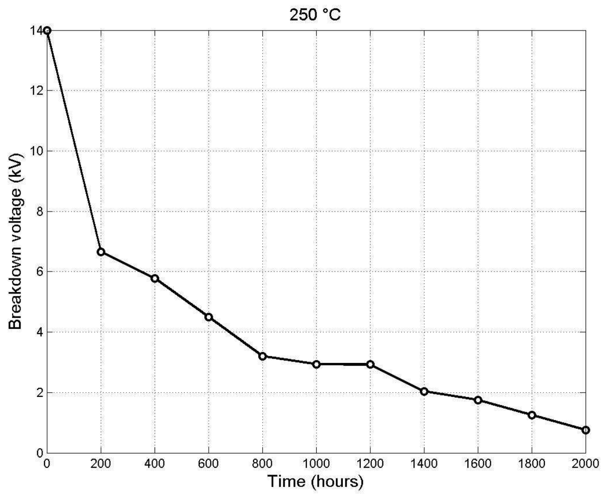

Figure 1. Mean value of breakdown voltage for 250 °C.

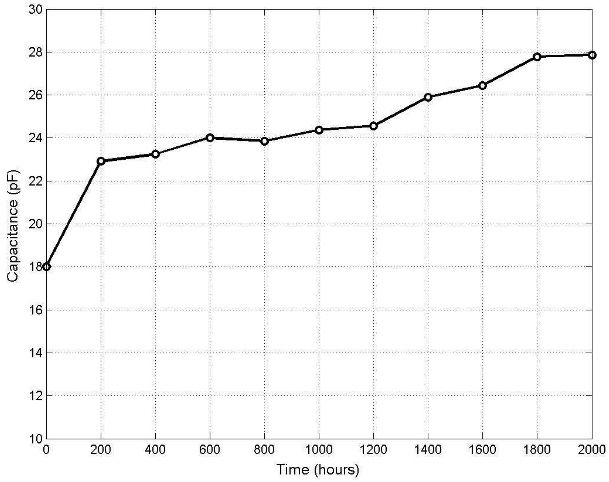

Figure 2. Mean value of the specimen capacitance for 250 °C..

2.2 ON-LINE MONITORING SYSTEM

The synopsis of the monitoring system is presented in Figure 3. The spectrum of the measured signal on a running machine has many low frequency spectrum lines, up to several kilohertz, corresponding to the slotting effects. However, it has no natural lines in the range of 100 kHz – 2 MHz, which corresponds to stator winding resonances [7, 10, 11]. To detect such phenomena a high frequency low-level voltage is superimposed to the stator supply, and the corresponding HF current and magnetic fields are measured. The injection system contains an inductance (L_{in}), which yields a series resonance depending on winding global capacitance Cg. Global capacitance Cg is determined by an identification of frequency response of three phases of the AC machine with an RLC circuit. The 4 kW studied machine has a global capacitance of 272 pF. The inductance Lin allows us to tune the series resonance frequency at a frequency higher than the parallel one, in this application Lin is chosen equal to 45 µH. Figure 4 shows series resonance with and without the injection inductance measured with a precision impedance analyzer Agilent 4294A between 100 kHz to 3 MHz; it can be observed that the series resonance induced by Lin is clearly identifiable.

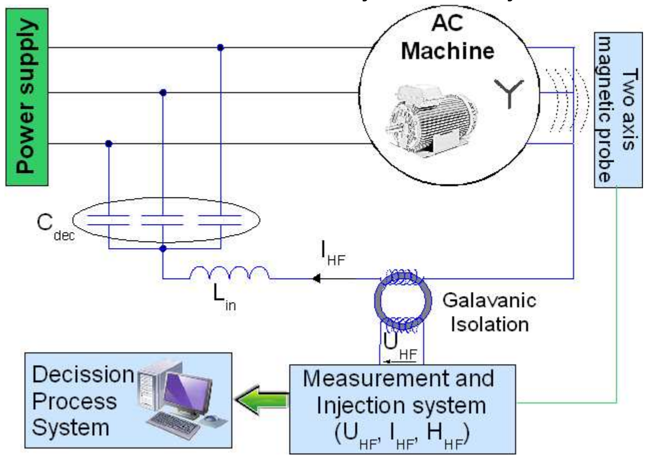

Figure 3. Synopsis of the monitoring system.

When the global equivalent capacitance varies, the series resonance varies in the same way as the parallel resonance. The coupling capacitor (C_{dec}) function consists in providing large impedance at inverter switching frequency (12 kHz) and a low impedance at series resonance frequency (≈1 MHz). A 10 nF/2 kV polypropylene film capacitor is chosen, its impedance is 1.6 kΩ at 10 kHz and 16 Ω at 1 MHz.

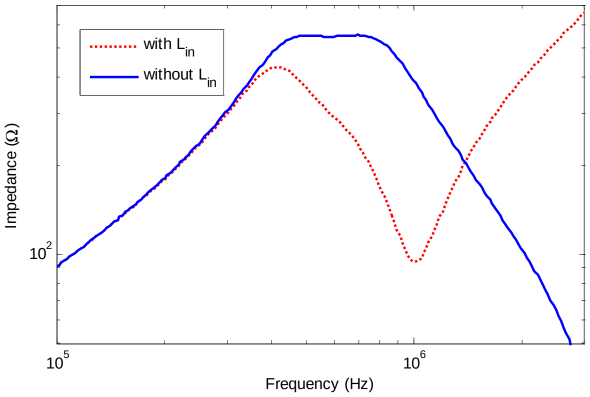

Figure 4. Impedance of AC machine with and without Lin.

The measurement and injection system is composed of a signal generator coupled with a HF amplifier. The signal generator is controlled by the decision process system and can apply a sinusoidal signal up to 2 MHz. Current measurement is performed by a passive current probe Tektronix P6022. Magnetic field is measured near the end-winding along two axes, denoted H1 and H2, described in Figure 5, the two axis magnetic sensor used is a Honeywell HMC1022 with a field range up to ±6 gauss and a sensitivity of 1 mV/V/gauss [12].

The first step consists in applying a sinus wave between 100 kHz to 2 MHz to determine for a sound AC machine a series resonance frequency deduced of impedance (current and voltage measurement) and magnetic fields H1 and H2. Then the frequency range is reduced around this first resonance frequency. For this study, a limited number of measurements have been realized for each stage of the aging of the machine.

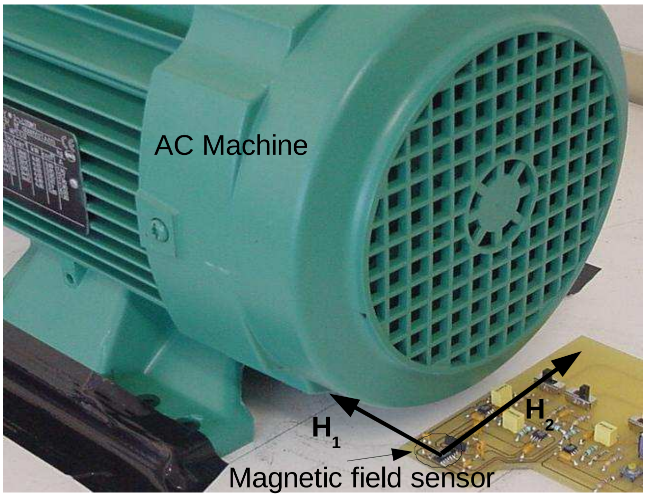

Figure 5. AC machine and magnetic field sensor position.

In an industrial context, these measures would be carried out continuously or during chosen periods. While the machine is working, the on-line monitoring system injects an HF sinusoidal signal around the resonance frequency of the machine. These measurements allow one to determine the variation of resonance frequency of the AC machine winding.

In the next section, these three estimations of the resonance frequency provided by the impedance and magnetic fields are combined in the framework of belief functions in order to improve the decision-making process regarding the winding aging.

3. AGING ESTIMATIONS FUSION

In this paper, the problem of information fusion is addressed using the Dempster-Shafer theory of belief functions [9], a rich and flexible framework for representing and reasoning with various forms of imperfect information and knowledge. Belief functions were first introduced by Dempster as a tool for statistical inference [13], and were later proposed by Shafer [8] as a general formalism for representing partial information and reasoning under uncertainty. Since then, different models based on the basic mathematical apparatus of belief functions have been proposed, including the Transferable Belief Model (TBM) [14] which is adopted here. A discussion of these interpretations of belief functions (TBM, Dempster's model, Hints model, random sets) can be found in [9].

The Transferable Belief Model (TBM) is a model of uncertain reasoning and decision-making based on two levels:

- the credal level, where available pieces of information are represented and manipulated by belief functions;
- the pignistic or decision level, where belief functions are transformed into probability measures when a decision has to be made.

The basic concepts of this model are exposed in the next section.

3.1. BELIEF FUNCTIONS: BASIC CONCEPTS

3.1.1. CREDAL LEVEL

Let $\Omega = \{\omega_1, \ldots, \omega_K\}$, called the frame of discernment or the universe, be a finite set of the possible answers to a given question Q of interest.

Information held by a rational agent Ag regarding the answer to question Q can be quantified by a mass function m defined on Ω, which is an application from 2^Ω to [0,1] verifying:

$$\sum_{A \subseteq \Omega} m(A) = 1. \qquad (2)$$

The quantity m(A) represents the part of the unit mass allocated to the hypothesis that the answer to question Q is in the subset A of Ω, and to no strict subset. The mass m(Ω) represents then the degree of total ignorance regarding the answer to the question Q of interest.

Let us remark that the mass on the empty set $m(\emptyset)$ may be positive. This mass plays a role of alarm in the TBM, the sources being conflicting [15].

Once each piece of information represented by a belief function, an aggregating operator can be used in order to synthesize and capture all the relevant information contained individually in each piece of information.

Two distinct mass functions m_1 and m_2 can be combined using the conjunctive rule of combination defined by:

$$m_1 \cap m_2(A) = \sum_{B \cap C = A} m_1(B)\, m_2(C), \quad \forall A \subseteq \Omega. \qquad (3)$$

This combination is associative and commutative, which ensures that the order the sources are combined does not affect the combination result.

For example, let us consider a universe $\Omega = \{\omega_1, \omega_2, \omega_3\}$, and two sources of information S_1 and S_2 providing respectively the pieces of evidence m_1 and m_2 such that $m_1(\{\omega_1,\omega_2\}) = 0.8$, $m_1(\{\omega_2\}) = 0.2$, $m_2(\{\omega_2,\omega_3\}) = 0.3$, and $m_2(\Omega) = 0.7$. Their combination can then be computed as illustrated by table 1.

Table 1. Conjunctive combination of m_1 and m_2

$m_1 \setminus m_2$	$\{\omega_2,\omega_3\}$ 0.3	Ω 0.7
$\{\omega_1,\omega_2\}$ 0.8	$\{\omega_1,\omega_2\}\cap\{\omega_2,\omega_3\}=\{\omega_2\}$ $0.8 \times 0.3 = 0.24$	$\{\omega_1,\omega_2\} \cap \Omega = \{\omega_1,\omega_2\}$ $0.8 \times 0.7 = 0.56$
$\{\omega_2\}$ 0.2	$\{\omega_2\}\cap\{\omega_2,\omega_3\}=\{\omega_2\}$ $0.2 \times 0.3 = 0.06$	$\{\omega_2\}\cap \Omega = \{\omega_2\}$ $0.2 \times 0.7 = 0.14$

The resulting mass function, denoted m, is therefore defined by $m(\{\omega_2\}) = 0.24 + 0.06 + 0.14 = 0.44$, and $m(\{\omega_1,\omega_2\}) = 0.56$. The mass supporting the state of the universe ω_2 has been reinforced with this combination.

3.1.2. DECISION LEVEL

When a decision has to be made regarding the answer to question Q, a strategy [14, 16] 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:

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

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:

$$BetP(\{\omega_2\}) = \frac{m(\{\omega_2\})}{1\ (1-0)} + \frac{m(\{\omega_1,\omega_2\})}{2\ (1-0)} = 0.44 + \frac{0.56}{2} = 0.72\ ;$$

$$BetP(\{\omega_1\}) = \frac{m(\{\omega_1,\omega_2\})}{2\ (1-0)} = \frac{0.56}{2} = 0.28\ .$$

It follows a decision in favor of ω_2.

3.2. FUSION MODEL FOR AC MACHINE WINDING AGING ESTIMATION

In the present fusion problem, the question Q of interest is the following: "Has the AC machine winding to be changed?" The universe Ω of the possible answers to question Q is then composed of two elements: Ω={yes,no}.

As mentioned in Section 2, the resonance frequency of a winding, obtained by impedance or magnetic fields, decreases over time. The measurements of resonance frequency based on these different techniques, constitutes then different opinions regarding the winding aging, which can be expressed as mass functions defined on Ω.

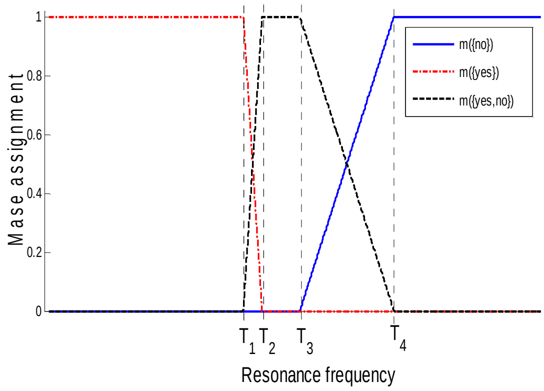

Figure 6. Mass assignment method allowing one to convert measurements on the resonance frequency of a winding, into a piece of information regarding the necessity to substitute this winding.

The mass assignment used in this paper, is based on four thresholds $(T_i)_{i\in\{1,2,3,4\}}$ depicted in Figure 6. For example, it can be observed in this figure, that if the measured resonance frequency is lower than T_1, the total part of the unit mass is allocated to the answer "yes, the winding has to be substituted".

Let us note that the resonance frequency measurements based on the impedance and magnetic fields, are generally associated with different vectors of thresholds. The determination of these thresholds can be realized by a human expert or a learning set composed of labeled resonance frequencies, that is, resonance frequencies associated with a known winding aging.

Thanks to this conversion, at each time t, the measurements of resonance frequency based respectively on impedance, magnetic fields H_1 and H_2, provide different pieces of information, expressed respectively by m_Z, m_1 and m_2, regarding the winding substitution necessity.

Once computed, these mass functions can be combined using the conjunctive rule of combination (equation (3)):

$$m(A) = m_Z \cap m_1 \cap m_2(A), \quad \forall A \subseteq \Omega. \qquad (5)$$

The resulting mass function m can then be transformed into the pignistic probability (equation (4)) to make the final decision.

For example, let us consider that the following mass functions have resulted from the mass assignment step:

- $m_Z(\{yes\})=0.6$ and $m_Z(\Omega)=0.4$ (from the resonance frequency measurement based on the impedance, the substitution of the winding is rather necessary);
- $m_1(\Omega)=1$ (from the resonance frequency measurement based on the first magnetic, there is a total ignorance regarding the necessity to replace the winding);
- $m_2(\{no\})= 0.1$ and $m_2(\Omega)=0.9$ (from the resonance frequency measurement based on the second magnetic field, the substitution of the winding is not really necessary).

Then, the conjunctive combination denoted m of m_1, m_2 and m_Z verifies:

$$m(\Omega) = 0.4 \times 1 \times 0.9 = 0.36\ ; \quad m(\{yes\}) = 0.6 \times 1 \times 0.9 = 0.54\ ;$$
$$m(\{no\}) = 0.4 \times 1 \times 0.1 = 0.04\ ; \quad m(\varnothing) = 0.6 \times 1 \times 0.1 = 0.06. \qquad (5)$$

The pignistic probability is thus given by:

$$BetP(\{yes\}) = \frac{1}{1-0.06}(0.54+\frac{0.36}{2}) = 0.77\ ;$$
$$BetP(\{no\}) \ = \frac{1}{1-0.06}(0.04+\frac{0.36}{2}) = 0.23\ . \qquad (6)$$

In this example, as BetP({yes})>BetP({no}), the winding has to be changed.

3.3. APPLICATION

At fifty different steps of the aging of the machine winding, three measurements of the winding resonance frequency have been realized from the three measured parameters (impedance, two magnetic fields). The ground truth is known: the first forty measurements correspond to a winding which has not to be changed, while the last ten are associated with a winding which has to be changed.

The Figure 7 illustrates the different resonance frequencies obtained for each measurement technique, as well as the ground truth. A winding associated with a resonance frequency lower than *95%* of the resonance frequency obtained when the winding is sound, is generally considered as to be changed. This limit is represented for each measurement technique as a horizontal line in Figure 7.

From Figure 7, it can be observed than an individual decision process:

- based on the impedance commits one error (measurement number 45);
- based on the first magnetic field commits two errors (measurement numbers 35 and 38);
- based on the second magnetic field commits three errors (measurement numbers 40, 41 and 42).

The goal of the fusion consists in improving these results by making fewer errors.

The Figure 8 illustrates the thresholds used to build the mass functions provided by the first magnetic field.

Thresholds used for the impedance and the second magnetic field are not detailed in the same figure for the sake of clarity.

The Figure 9 depicts the pignistic probabilities obtained for each measurement. It can be observed that:

- for each measurement where the winding has not to be changed, BetP({no})>0.5 ;
- for each measurement where the winding has to be changed, BetP({yes})>0.5.

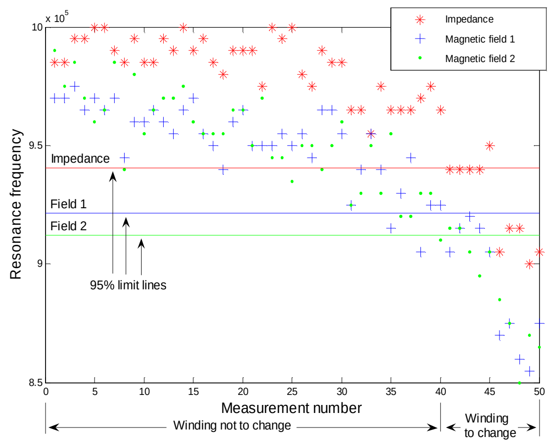

Figure 7. Resonance frequencies obtained at 50 different steps of the aging of the machine winding

Thus, on this particular test, this fusion made zero error whereas each individual decision process made at least one error, which fulfills its purpose.

Let us note that in this same application a simple fusion based on a majority vote leads to zero error as well. A more

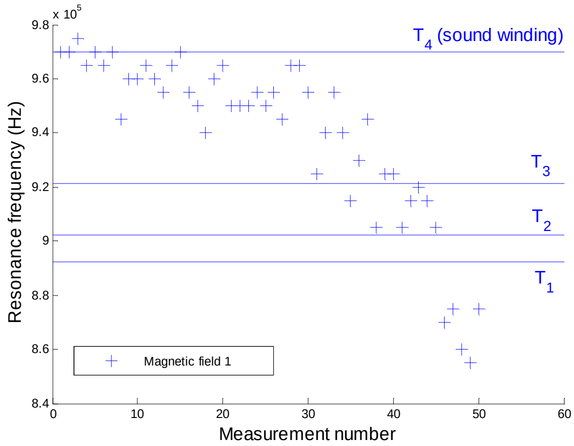

Figure 8. Thresholds used to build the mass function provided by the first magnetic field.

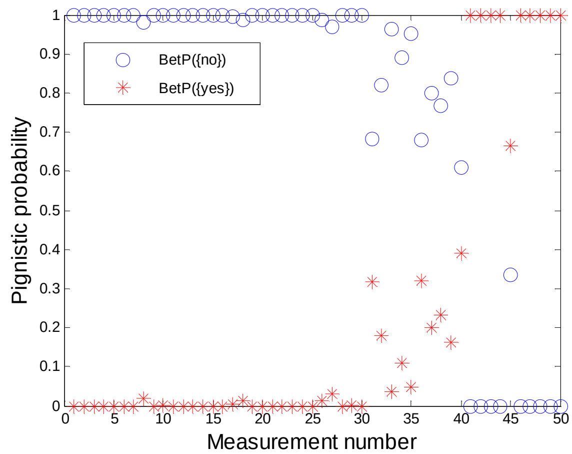

Figure 9. Pignistic probabilities at fifty different steps of the aging of the machine winding after combining the three measurements based on the

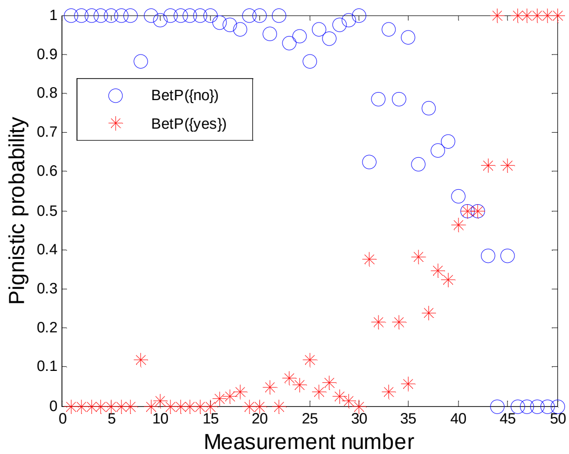

Figure 10. Pignistic probabilities at the same fifty different steps of the aging of the machine winding after combining the measurements based

complex application test should be undertaken to validate this approach.

Nevertheless some interesting points of this fusion already appear:

- This fusion method based on belief functions provides a degree of reliability in addition to its decisions
- It also allows one to combine only two sources of information which is more difficult to realize with a voting system. Let us suppose the failure of a sensor, for example the current measurement. The Figure 10 represents the pignistic probability resulting from the combination of the two masses m_1 and m_2 coming from the two magnetic fields. It can be observed that no error are committed, however there is an ambiguity on the measurements 40 and 41, where BetP({no})= BetP({yes})=0.5. This last fusion can also be interesting if we consider a price for the measurements. The value in money may be better by not measuring the resonance frequency from the impedance, the gain in terms of robustness and performance remaining sufficient.

4. CONCLUSION

The paper has presented an on-line diagnostic system of AC machine based on the fusion of HF measurements providing evidence regarding the winding aging. This system has shown a reliable and robust diagnostic on a "real world" test. The next step of this study consists in implementing this system in an industrial application to validate this approach on more experimental data. Further studies can also be undertaken to develop the fusion model by taking into account the reliabilities of each measurement [17] or the temporal aspect of the measurements for example.

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