Diagnostic Based on High Frequency Resonances and Information Fusion

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). A new monitoring system able to detect slight variations of high frequency resonances in the winding of a working machine fed by an industrial inverter was presented in [1]. Several measurements can be used in order to estimate the aging of an AC machine winding (HF measurements of current or magnetic field) [2]. When a measure, also called a piece of information, is precise and certain, no other measure is necessary. However, such a measure is rarely obtained in real world application. 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 [3,4]. In this paper, different measurements of the aging of an AC machine winding are combined in the latter frame. This approach is tested on real measurements.

I. INTRODUCTION

Stator insulation failures involve about one third of the total number of AC machines outages in industrial environment [5]; 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 [6]. 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 [5], 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 [7] or to follow the PD activity on a high voltage working machine [8] or with off-line PD testing systems [9].

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. Results of the measurements made on a typical magnet wire [1], 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. This method is tested on data resulting from measurements on a machine of 4 kW inverter fed machine, and allows us in particular to obtain a more robust and reliable diagnostic.

II. INFLUENCE AGING ON AC MACHINE AND MONITORING SYSTEM

A. Influence aging of AC machine

Thermal accelerated aging was performed in previous study on specimens made with a polyesterimide (THEIC) magnet wire according to the IEC 60851-5 standard [1]. 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. A model which was developed in [1] shows that the capacitance variation of winding machine induces a modification of the frequencies characteristic. This variation is significant and can be exploited. 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 RLC parallel equivalent circuit that represents the winding first resonance. For a frequency range from 1 kHz to 10 MHz, a simple parallel RLC equivalent circuit represents roughly the machine winding frequency behavior [2] Our purpose is to determine the influence of the turn-to-turn capacitance on the global capacitance Cg defined by the RLC parallel equivalent circuit. Cg is a function of turn-to-turn capacitance Ci and turn to magnetic core capacitance Cm:

$$Cg = f(Ci, Cm) \tag{1}$$

The numerical value of Ci is much higher than Cm. 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.

B. On line monitoring system

The synopsis of the monitoring system is presented in Fig. 1. 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 [1, 2]. 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 (Lin), 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 L_{in} is chosen equal to 45 μH . Fig. 2 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 L_{in} is clearly identifiable. 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 (~1MHz). A 10 nF/2 kV polypropylene film capacitor is chosen, its impedance is 1.6 k Ω at 10 kHz and 16 Ω at 1 MHz.

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 2MHz. Current measurement is performed by a passive current probe Tektronix P6022. Magnetic field is measured near the end-winding along two axes, denoted $\rm H_1$ and $\rm H_2$, described in Fig. 3, 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.

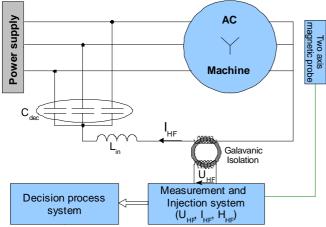


Fig. 1. Synopsis of the monitoring system

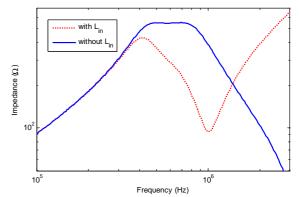


Fig. 2. Impedance of AC machine with and without Lin.

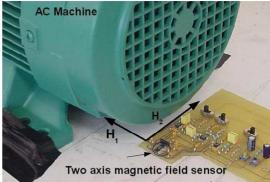


Fig. 3. AC machine and magnetic field sensor position.

The first step is to apply a sinus wave between 100kHz to 2MHz to determine for a sound AC machine a series resonance frequency deduced of impedance (current and voltage measurement) and magnetic fields H_1 and H_2 . 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. 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 aging of a winding.

III. AGING ESTIMATIONS FUSION

A. Belief functions: basic concepts

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:

$$\sum_{A \subset O} m(A) = 1 \tag{2}$$

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. For example, the mass $m(\Omega)$ represents the degree of ignorance regarding the answer to the question of interest.

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

$$m_1 \cap m_2(A) = \sum_{B \cap C = A} m_1(B) \ m_2(C), \quad \forall A \subseteq \Omega.$$
 (3)
This combination is associative and commutative, which

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

When a decision has to be made regarding the answer to question Q, a strategy [10,11] 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:

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

The chosen decision is then the one that maximizes betP.

B. 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: $\Omega = \{yes, no\}$.

As mentioned in Section II, 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 .

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

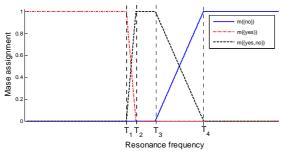


Fig. 3. Mass assignment method allowing one to convert measurements on the resonance frequency of a winding, into a piece of information regarding the necessity to substitute this winding.

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 (3):

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

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

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 impedance point of view, the substitution of the winding is rather necessary);
- $m_I(\Omega)=1$ (the first magnetic field has a total ignorance regarding the necessity to replace the winding);
- $m_2(\{no\})=0.1$ and $m_2(\Omega)=0.9$ (from the second magnetic field point of view, the substitution of the winding is not really necessary).

Then:

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

and:

$$BetP(\{yes\}) = \frac{1}{1 - 0.06} (0.54 + \frac{0.36}{2}) = 0.77 ;$$

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

Thus the winding has to be changed.

C. Application

At 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. Fig. 4 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 Fig. 4.

From Fig. 4, 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 committing fewer errors. Fig. 5 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 being not detailed in the same figure for the sake of clarity. Fig. 6(a) depicts the pignistic probabilities obtained for each measurement. It can be observed that:

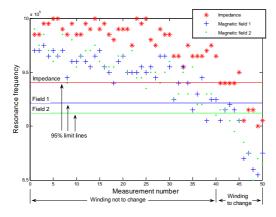


Fig. 4. Resonance frequencies obtained at 50 different steps of the aging of the machine winding.

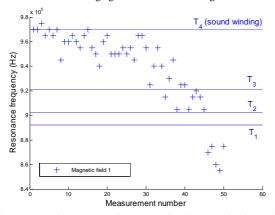


Fig. 5. Thresholds used to build the mass function provided by the first magnetic field.

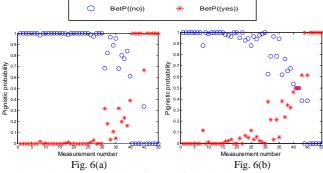


Fig. 6. Pignistic probabilities after combining, the three measurements (Fig. 6(a)), and after combining only the measurements coming from the two fields (Fig. 6(b)).

- 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, $BetP({yes})>0.5$.

Thus, this fusion made zero error which fulfills its purpose. Let us note that a fusion based on a majority vote leads also to zero error in this application. However, the fusion based on belief functions provides a degree of reliability in addition to the decision, and allow one to combine only two sources as explained below.

In the case of the failure of a sensor, for example the current measurement, it can be interested to examine the combination of only the two magnetic fields. Fig. 6(b) represents the pignistic probability obtained by this fusion strategy. It can be observed that no error are committed, however there is an ambiguity on the measurements 40 and 41, where $BetP(\{no\}) = BetP(\{yes\}) = 0.5.$

IV. CONCLUSION

The paper presents an on-line diagnostic system of AC machine. Decision system process based on information fusion provides a reliable and robust diagnostic. The next step of this study consists in implementing this system in an industrial application to validate this approach on more experimental data.

REFERENCES

- [1] F. Perisse, D. Roger, P. Werynski, "A New Method for AC Machine Turn Insulation Diagnostic Based on High Frequency Resonances", IEEE Transactions on Dielectrics and Electrical Insulation, Vol. 14, N°. 5, October 2007, pp1308-1315.
- [2] F. Perisse, D. Roger, C. Saligot, "Online testing of AC motor for predictive maintenance" *Electromagnetic Fields in Mechatronics*, Electrical and Electronic Engineering, "Studies in Applied Electromagnetics and Mechanics", Volume 27 IOS Press, August 2006, ISBN: 1-58603-627-0.
- G. Shafer, "A mathematical theory of evidence", Princeton University Press, Princeton, N.J., 1976.
- Ph. Smets, "What is Dempster-Shafer's model?". In R. R. Yager, J. Kacprzyk, and M. Fedrizzi, editors, Advances in the Dempster-Shafer theory of evidence, 1994, pp. 5-34.
- G.C .Stone, E.A. Boulter, I. Culbert, H. Dhirani, "Electrical Insulation for Rotating Machines", IEEE Press Series on Power Engineering, 2004.
- R.M. Tallam et all. "A survey of methods for detection of stator related faults in induction machines," Symposium on Diagnostics for Electric machines, Power Electronics and Drives, SDEMPED, Atlanta, GA,USA, 24-26 August 2003, pp.35 - 46.
- E. Wiedenbrug, G. Frey and J. Wilson, "Impulse testing and turn insulation deterioration in electric motors", *Pulp and paper industry Technical conference*, 16-20 June 2003, pp. 50 – 55.
- A. Cavalini, G.C. Montanari, F. Puletti, A. Contin, " A new methodology for the identification fo PD in electrical apparatus: properties and applications", IEEE Trans. on Dielect. Elect. Insulation, Vol. 12 No. 2, April 2005, pp.203 – 215.
- C. Hudon, N. Amyot, T. Lebey, P. Castelan and N. Kandev, "Testing of low-voltage motor turn insulation for pulse-width modulated applications", *IEEE Trans. on Dielect. Elect. Insulation*, Vol. 7, No. 6, Dec. 2000, pp. 783 – 789.
 [10] T. Denœux, "Analysis of evidence-theoretic decision rules for pattern
- classification". Pattern Recognition, Vol 30 No. 7, 1997, pp. 1095-1107.
- Ph. Smets and R. Kennes. "The Transferable Belief Model". Artificial Intelligence, Vol 66, 1994, pp.191-243.