A Belief Function Solution for Stator Insulation Robustness Study

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***Abstract*— This paper proposes a model-based decision taking solution for electrical machines winding insulation robustness study. The solution is based on the Belief Function (BF) theory. It is processed in two main steps: a first one aims to learn Weibull model parameters from some labeled aging Partial Discharge Inception Voltage (PDIV) data. Then a second classification step separates some unlabeled PDIV data according to the learnt Weibull models. The classification results can give information on the robustness and the reliability of the Electrical Insulation System (EIS) under a thermal constraint.**

Keywords—belief function, stator insulation, Weibull parameters, partial discharges, electrical machines, aging.

I. INTRODUCTION

The aging of electrical machine is characterized by physical and chemical modifications, which reduce its lifetime, and therefore, its ability to operate without risk of failure [1]. The IEC 60505 standard describes the different types of EIS aging the basis for estimating it [2].

The evolution towards a more electric aircraft leads to increase the electric power transported by the onboard network. Therefore, the voltage is elevated, from 115V AC to 540V DC. Consequently, static converters cause more drastic electrical constraints on all the Electrical Insulation Systems (EIS) and induce the appearance of Partial Discharges (PD) and premature aging of the EIS and electrical machine damage [1, 2].

In addition to the electrical constraint, the thermal constraint is also inherent to electrical machines empowering. Under this constraint, the physical and chemical characteristics of the EIS can be modified and may lead to a premature appearance of PD and machine damage [1]. Multiple studies on the thermal constraint effect on the EIS are achieved and propose empirical models [l - 5]. They are generally based on Arrhenius empirical law which assumes that the activation energy, in chemical EIS reactions, is a proper constant of the material and does not depend on the temperature [6]. However, different aging phenomena occur at the high temperatures. They are characterized by different activation energies than during normal use [7].

Beside the empirical models, this paper proposes a statistics based modeling, using the Weibull rule and a decision taking solution based on Belief Function (BF) theory. The BF theory is known to be more general than probability theory. It is already used for electrical machines diagnosis purpose where sensors measurements are fused in BF framework in order to detect short-cuts in machines stators [8].

In the proposed paper, the BF theory is used to study the robustness of stators winding insulation against thermal constraint. Firstly, BF theory is defined and a classification method is proposed. The classifier uses PDIV data obtained from a standard thermal accelerated aging process of two different enameled wire insulations. The results give some motivation of new applications of the proposed solution.

II. BASICS ON BELIEF FUNCTION THEORY

Belief function theory is also referred to as Dempster-Shafer theory on behalf of Arthur Dempster and Gleen Shafer who introduced the theory [9, 10]. In 90's the theory is studied and formulated as a Transferable Belief Model (TBM) by Philippe Smets [11]. In this section, we describe some basic functions of the TBM.

A. Belief representation

Knowledge on a random variable X taking values in a finite set $\Omega = \{\omega_1, \omega_2, \ldots\}$, is represented by a mass function defied by: $m: 2^{\Omega} \rightarrow [0,1]$ verifying:

$$\sum_{A \in \Omega} m(A) = 1 \qquad (1)$$

Sets $A \subseteq \Omega$ with $m(A)>0$ are called focal elements. If $m(\emptyset)>0$, the mass function is not normalized, it can be normalized as follows:

$$m^*(A) = \frac{m(A)}{1-m(\emptyset)}, \quad \forall A \subseteq \Omega, A \neq \emptyset, \qquad (2)$$

With $m^*(\emptyset)=0$. Belief function *bel* and plausibility function pl are two alternative representations of belief functions:

$$bel(A) = \sum_{B \in A,\, B \neq \emptyset} m(B), \quad \forall A \subseteq \Omega \qquad (3)$$

$$pl(A) = \sum_{B \cap A \neq \emptyset} m(B), \quad \forall A \subseteq \Omega \qquad (4)$$

Where bel(A) represents the amount of knowledge which completely agree with A and pl(A) represents the amount of knowledge which does not contradict A.

B. *Belief contsruction using the GBT*

The Generalized Bayes Theorem (GBT) proposed by Smets in [12] allows one to construct a belief function from likelihood functions. Given some observations Z, the likelihood function $L(Z|\omega_i)$ is seen as a plausibility function $pl[\omega_i](Z)$ in belief function theory [5]. Knowing the observations Z, a mass function on Ω can be constructed using:

$$m[Z](A)=\prod_{\omega_i\in A}(pl[\omega_i](Z))\left(1-\prod_{\omega_i\in \bar{A}}(1-pl[\omega_i](Z))\right) \quad (6)$$

With $A\subseteq\Omega$.

C. *Belief combination and decision taking*

Dempster's rule of combination in (7) is commonly used to fuse mass functions from multiples sources. Mass functions m_1 and m_2 from two different sources are combined as follows:

$$m_1\oplus m_2(A)=\frac{\sum_{A_1\cap A_2=A} m_1(A_1)m_2(A_2)}{1-\sum_{A_1\cap A_2=\emptyset} m_1(A_1)m_2(A_2)} \quad (7)$$

With $\forall A_1,A_2\subseteq\Omega$. Other combination rules can also be used [11 - 13]. For decision purpose, a mass function can be transformed into pignistic probabilities as follows:

$$Betp(\omega)=\sum_{\omega\subseteq A,\ A\subseteq\Omega}\frac{m(A)}{|A|(1-m(\emptyset))}, \quad (8)$$

Other decision taking strategies can also be considered [11]. In the proposed solution, pignistic probabilities are used.

III. Proposed Solution

The proposed solution aims to extract knowledge, regarding the stator insulation characteristics, from some PDIV data. Firstly, some supervised (labelled) data are used to learn classes Weibull models using the Maximum likelihood Estimation (MLE). Secondly, according to the learnt models, we classify some unsupervised (unlabeled) data which are obtained in different physical thermal conditions. These two main steps and an illustrative example are given in this section.

A. *Learning Step*

This step aims to estimate the parameters β,η of Weibull model, using the MLE algorithm. Given a set $Z=\{z_1,z_2,\ldots,z_n\}$ of observations, the MLE algorithm estimates the parameters β,η which maximizes the following likelihood function:

$$L(\beta,\eta|Z)=\prod_{i=1}^{n}\frac{\beta}{\eta}\left(\frac{z_i}{\eta}\right)^{\beta-1}e^{\left(\frac{z_i}{\eta}\right)^{\beta}} \quad (9)$$

One can learn as many models as many known classes, for n classes, n models have to be learnt: $c_j=\{\beta_j,\eta_j\}$, j=1,…n.

In our case, the classification can be done regarding the wire diameter, the insulation material, etc.

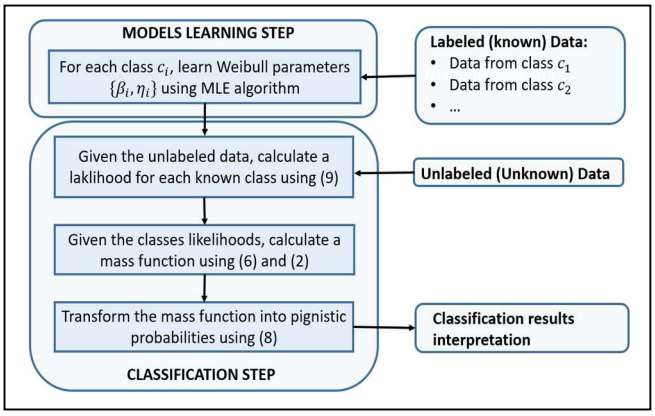
B. *Classification step*

The classification step is performed in the belief function framework. It aims to determine the class of some unknown (unlabeled) observations contained in the set $X=\{x_1,x_2,\ldots,x_n\}$. It is processed in three main steps:

1. Given the learnt models and the unknown data X, calculate the likelihood functions using (9).
2. Given the likelihood functions, a masse function is calculated using the GBT in (6) and normalized using (2).
3. When a decision needs to be taken, the mass function is transformed into pignistic probabilities using (8).

The proposed solution is summarized in the following flowchart.

Fig.1 Flowchart of the proposed classification method.



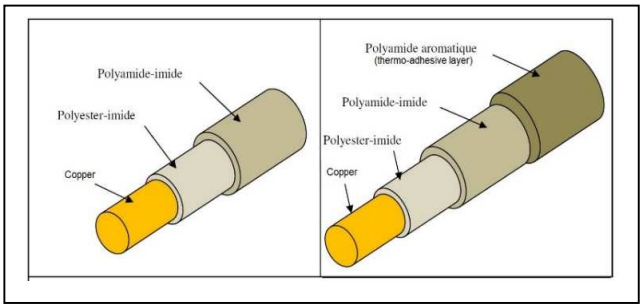
IV. Experimental Part and Results

This section firstly describes the experimental part from [14, 15] and how PDIV data are obtained, then a numerical application example of the proposed solution is given. At last, some classification results are discussed.

A. *Experimental part*

In this section we consider the experiment performed in [14, 15] where an accelerated thermal aging process is performed on a large number of twisted pairs of enameled wires. Two kind of wires are considered and are represented in Fig.2: a classical wire composed of copper, with polyester-imide and polyamide-imide layers, and a so-called thermos-adhesive wire having a polyamide aromatic layer in addition to the classical composition.

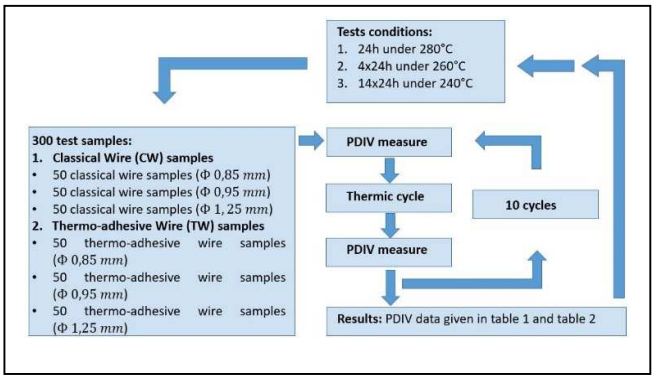
Fig.2 Representation of the studied Classical and Thermo-adhesive wires



from [14].

The thermal aging process is performed on 300 samples: 150 for the classical wire with three different diameters (0.8mm,

0.95mm and 1.25mm) and 150 for the thermos-adhesive wire with three different diameters (0.8mm, 0.95mm and 1.25mm). The aging process is represented in Fig.3, it is realized according to IEC 60172 and IEC 60270 standards [16, 17]. The process outputs Partial Discharge Inception



Voltages (PDIV) where the average values are given in Table I and Table II.

Fig.3 Description of the thermal aging process.

The average values of the PDIV measures are given in Table I for the Classical Wire (CW) and in Table II for the Thermo-adhesive Wire (TW).

TABLE I. THE AVERAGE PDIV FOR THE CLASSICAL WIRE (CW).

	Cycles of 1 day under T=280°C							
Days:	0	1	2	3	4	5	6	7
CW Φ 0.85 mm	720	623	578	565	529	498	469	450
CW Φ 0.95 mm	651	545	490	475	453	414	400	380
CW Φ 1.25 mm	694	614	560	546	495	459	416	
	Cycles of 4 days under T=260°C							
Days:	0	4	8	12	16	20	24	
CW Φ 0.85 mm	644	578	571	549	526	493	491	
CW Φ 0.95 mm	568	499	477	440	432			
CW Φ 1.25 mm	628	568	545	534	508	489	482	
	Cycles of 14 days under T=240°C							
	0	14	28	42	56	70		
CW Φ 0.85 mm	740	672	648	615	598	565		
CW Φ 0.95 mm	635	583	543	516	518	498		
CW Φ 1.25 mm	670	625	600	567	574	537		

TABLE II. THE AVERAGE PDIV FOR THE THERMO-ADHESIVE WIRE (TW).

	Cycles of 1 day under T=280°C							
Days:	0	1	2	3	4	5	6	7
TW Φ 0.85 mm	740	592	547	544	513	490	457	443
TW Φ 0.95 mm	712	613	547	531	501	463	436	400
TW Φ 1.25 mm	722	608	563	552	505	460	408	
	Cycles of 4 days under T=260°C							
Days:	0	4	8	12	16	20	24	
TW Φ 0.85 mm	645	545	544	542	494	478	438	
TW Φ 0.95 mm	652	561	554	531	521	493	475	
TW Φ 1.25 mm	674	555	538	523	503	434		
	Cycles of 14 days under T=240°C							
	0	14	28	42	56	70		
TW Φ 0.85 mm	734	632	610	591	571	550		
TW Φ 0.95 mm	715	596	567	547	567			
TW Φ 1.25 mm	711	614	567	556	530			

B. Application example of the proposed solution

Let us consider two different classes corresponding to two different insulation materials.

C={Classical wire (CW), Thermo-adhesive Wire (TW)}.

Let us take as learning data rows 2 from Table I and Table II, respectively for the classes CW and TW. The whole solution is processed as follows:

- Weibull models learning using (9): for the class CW=$\{\beta_1,\eta_1\}$, the estimated shape parameter is β_1= 5.6942, with lower and upper bounds estimation [3.4521, 9.3926], and the estimated scale parameter is η_1=512.1009, with lower and upper bounds estimation [449.9045,582.8955]. For the class TW=$\{\beta_2,\eta_2\}$, the estimated shape parameter is β_2=5.7252 , with lower and upper bounds estimation [3.4343,9.5444], and the estimated scale parameter is η_2=565.8906 , with lower and upper bounds estimation [497.6129,643.5368].
- Calculate a mass function m[X]: $2^C \rightarrow [0,1]$ using the GBT (6) and normalize using (2). If we take for example as unknown (test data) the last row in Table II, we obtain the following mass function:

m[X](A)	{∅}	CW	TW	{CW, TW}
Value:	0	0.0016	0.958	0.396

The obtained mass function gives an idea on the uncertainty and the imprecision (joint effects) concerning the tested data.

- In order to take a decision, we calculate the pignistic probabilities using (8), which gives:

Betp[X](c)	CW	TW
Value:	0.0214	0.9786

Weibull plots of the models learnt in this example are given in Fig.4.

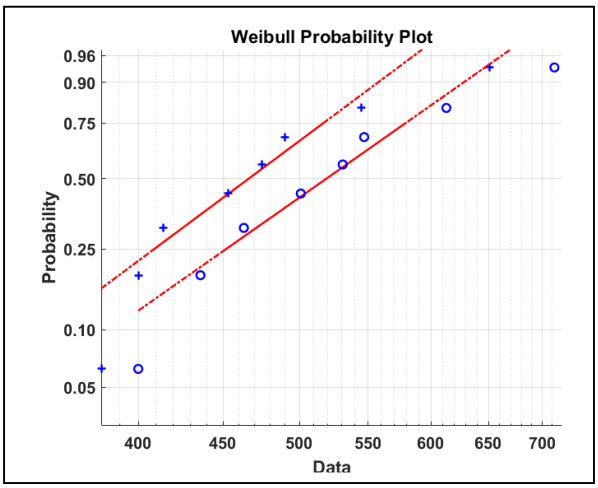


Fig.4 Weibull plot: symbols "o" correspond to TW data and symbols "+" correspond to CW data.

Fig.4 gives a first information where the TW seems to be more robust than CW: under T=280°C, the Classical Wire has 50% risk to have Partial Discharges (PD) at around 470V where the Thermo-adhesive Wire has the same risk at 520V. This result gives us a first information about CW and TW robustness.

C. Simulation Results

This section provides two main simulations where the first one aims to classify the data, in Table I and Table II, according to their insulation materials and the second one classifies the data, of each table separately, according to the wire diameter.

C.1 Classification according to the insulation materials

Using the two learnt CW and TW models in Section IV.B, the classification algorithm is applied to the data in Table I and Table II. Correct classification rates over 100 Monte-Carlo simulations, where the training data is picked randomly, are given in Fig.5.

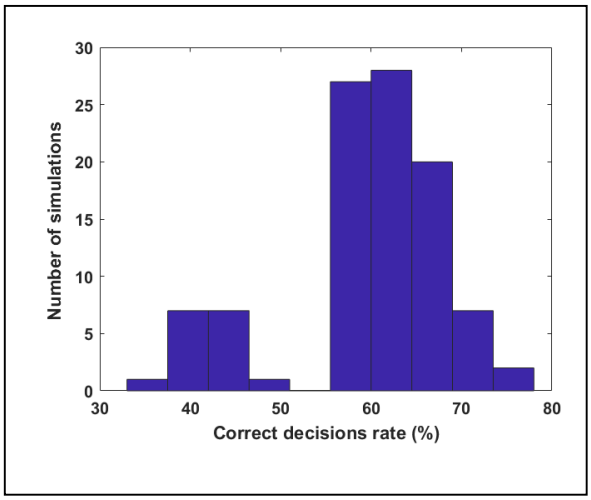


Fig.5 Correct classification rates over 100 Monte-Carlo simulations for CW and TW data

In about 80% of the simulations, the correct classification rate is higher than 50% as shown in Fig.5. The average correct decision is about 62%. This means that the data are broadly separated into two classes (CW and TW). This result means that behavior of the Classical Wire and the Thermo-adhesive Wire under the thermal constraint is different. Combined to the result of Fig.4, it can be said that the Thermo-adhesive Wire is more robust than the Classical Wire. Moreover, the classification rates give an idea on the robustness proportions.

C.2 Classification according to the wire diameter

The proposed solution in this section is used to separate the data of the Table I and the Table II according to the wire diameter. We consider then a set of three classes $C = \{0.85mm, 0.95mm, 1.25mm\}$. For Classical Wire data in Table I, three different diameters data sets are randomly picked for the learning step, then the classification step is processed over 100 Monte Carlo simulation. The same operations are applied to the Thermo-adhesive data in Table II. The classification results are given in Fig.6 for the CW data and in Fig.7 for the TW data.

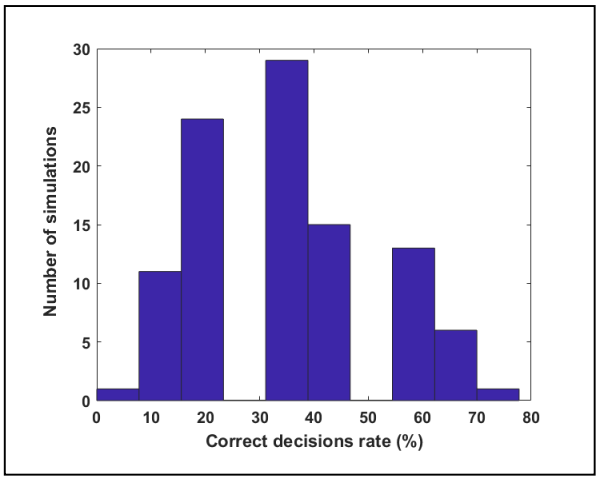


Fig.6 Correct classification rates over 100 Monte-Carlo simulations CW diameter data.

The average correct classification is about 35% in this simulation, as it can be seen in Fig.6. In about 21 simulations over 100, the correct classification rate is higher than 50%. This is a low recognition rate which may mean that the Classical Wire diameter does not have a significant impact on the EIS robustness under the thermal constraint.

The same conclusion can be made regarding the results of Fig.7 where we obtain an average of 32% of correct decisions and in about 1 simulation over 100, the correction decision rate is higher than 50%. This means that impact of the diameter on EIS robustness for the Thermos-adhesive Wire is even more insignificant.

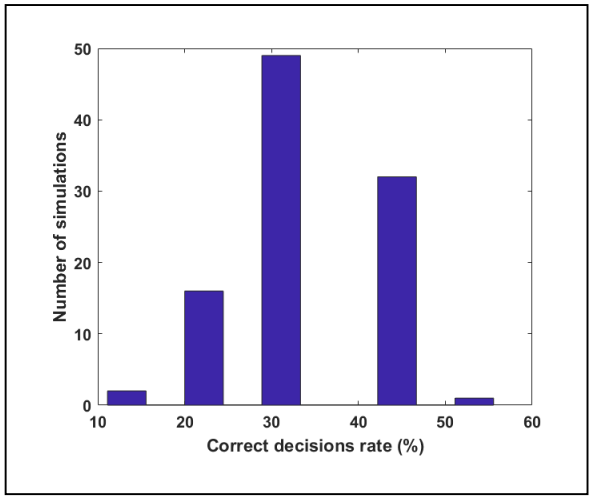


Fig.7 Correct classification rates over 100 Monte-Carlo simulations TW diameter data.

V. CONCLUSION

This paper provides a model based approach to study the stators EIS robustness under thermal constraint. The proposed solution is tested on two EIS data sets and show some interest in robustness study and quantification. This is a generic approach which can be applied to study other effects under electrical constraint, mechanical constraint, chemical constraint, etc.

The proposed solution may also be applied to study the joint effects on the EIS since it uses Belief Function theory. In fact, as illustrated in III.C, BF theory can quantify the joint effects on the EIS by giving weights to subsets or sets of hypotheses, for example the set {CW, TW} in III.C. In this case, the weight on {CW, TW} represents the degree of ignorance. In other examples, it can represent the joint effects or the correlation degree of multiple effects. This is an advantage which is not handled in probability theory where weights are given to singletons only.

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REFERENCES

[1] G. C. Stone, I. Culbert, E. A. Boulter, H. Dhirani, " Electrical insulation for rotating machines-design, evaluation, aging, testing, and repair", Wiley-IEEE Press, 2014.

[2] IEC60505- Evaluation and qualification of electrical insulation systems, 2011.

[3] L. A. Dissado, J. C. Fothergil, *Electrical degradation and breakdown in polymers*, IET Material and Device Series 9, 2008.

[4] P. Maussion and A. Picot and M. Chabert and D. Malec, ”Lifespan and aging modeling methods for insulation systems in electrical machines: A survey,” IEEE Workshop on Electrical Machines Design, Control and Diagnosis, pp. 279-288, 2015.

[5] N. Lahoud and J. Faucher and D. Malec and P. Maussion, “Electrical Aging of the Insulation of Low-Voltage Machines: Model Definition and Test With the Design of Experiments,” IEEE Transactions on Industrial Electronics, 60(9): 4147-4155, 2013.

[6] M. Celina, K. T. Gillen, R. A. Assink, "Accelerated aging and lifetime prediction: Review of non-Arrhenius behaviour due to two competing processes", *Polym. Degr. and Stab.*,90: 395-404, 2005.

[7] L. Tshiloz, A.C. Smith, P.M. Tuohy, T. Feehally. “Investigation of Wire Insulation for High Temperature Motor Windings”. In The Journal of Engineering, 2019(17) : 4442-4445,2019.

[8] M. Irhoumah, R. Pusca, E. Lefevre, D. Mercier, R. Romary, C. Demian, "Information fusion with belief functions for detection of inter-turn short circuit faults in electrical machines using external flux sensors", IEEE Transaction on Industrial Electronics, 65(3): 2642-2652, mars 2018.

[9] A. P. Dempster. “Upper and lower probabilities induced by a multivalued mapping”. The Annals of Mathematical Statistics, 38(2): 325–339, April 1967.

[10] G. Shafer. “A mathematical theory of evidence”. Princeton university press, 1976.

[11] P. Smets and R. Kennes. “The transferable belief model”. Artificial intelligence, 66(2):191–234, 1994.

[12] P. Smets. “Belief functions: the disjunctive rule of combination and the generalized bayesian theorem”. International Journal of Approximate Reasoning, 9(1): 1–35, 1993.

[13] T. Denœux. “Conjunctive and disjunctive combination of belief functions induced by nondistinct bodies of evidence”. Artificial Intelligence, 172(2): 234–264, 2008.

[14] S. Savin. “New indicator of aging of inter-turn insulation of electrical machines used in aeronautics”. PhD thesis, 2013.

[15] S. Savin, S. Ait-Amar and D. Roger, "Turn-to-turn capacitance variations correlated to PDIV for AC motors monitoring," in *IEEE Transactions on Dielectrics and Electrical Insulation*, 20(1): 34-41, February 2013.

[16] IEC 60172, “Test procedure for the determination of the temperature index of enamelled and tape wrapped winding wires", ed, 2015.

[17] IEC 60270 - High-voltage test techniques. Partial discharge measurements, 2001.