NOVEL METHOD FOR OVERALL CONDITION ASSESSMENT OF POWER TRANSFORMERS

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Abstract: Condition assessment is one of the key aspects behind the life cycle management of power transformers, as by means of condition assessment well-founded asset management decisions can be taken. For condition assessment different monitoring and diagnostic methods are applied. Thus, a systematic integration of all techniques is necessary. However, existing methodologies for condition assessment do not consider the required combination of all monitoring and diagnostic methods in a single approach. As a contribution to this necessity, in this paper a novel method for condition assessment based on multi-agent systems is presented. The application of the proposed method is also exemplified by means of a real case study. The obtained results are very encouraging as the proposed method allows combining systematically the outcome of the diagnostic methods and as a result a numerical value called condition index representing the healthiness state of a transformer is obtained.

1 INTRODUCTION

A condition assessment (CA) task consists in performing a set of diagnostic tests in order to diagnose the healthiness state of assets during their life cycle. In the literature some methods for CA in the form of a scoring system (usually called "condition index", CI) have been reported [1-2]. However, the existing methods do not consider the integration of all on-line monitoring and diagnostic methods in a single approach. Hence, the necessity of developing methods under which monitoring and diagnostic methods are combined and inter-related with each other was identified. As a contribution to this necessity, a novel method for CA called AICA (automatic and intelligent condition assessment) based on multi-agent systems was developed by the authors. Under a multi-agent environment, each monitoring and diagnostic technique is seen as an agent able to provide a judgment on the condition of the transformer. At the same time, each agent is developed using artificial intelligence and data mining techniques taken as base the knowledge collected along the years by the human experts (i.e. interpretation limits provided by standards) and data stored in databases.

This contribution presents an overview to the methodology behinds of AICA and its application. The paper is structured in 6 sections. The section 2 introduces the method WCCM used by AICA for the combination of diagnostic methods. Then the section 3 presents a matrix of detection and diagnosis of failure modes (DEDIFA) under which AICA establishes the inter-relation among diagnostic methods and subsequently in section 4 the methodology of AICA is briefly described. The section 5 illustrates the application of AICA by means of a real case study of CA of a 315 MVA, 400/220/33 kV autotransformer and finally in section 6 conclusions are provided.

2 WEIGHTED-CLASS CONSENSUS METHOD

In this section a new method called "weighted-class consensus method (WCCM)" is proposed as a methodology allowing the combination of diagnostic methods. For that, each diagnostic method is here considered as an intelligent agent. By definition, an agent is defined as a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its delegated objectives [3]. The block diagram of the WCCM method is shown in Figures 1. As can be appreciated, for each agent consisting of "m" members an agent consensus is carried out and subsequently, the outcome of the agent consensus is combined by a multi-agent consensus, which is in charge of issuing a final decision (i.e. classification).

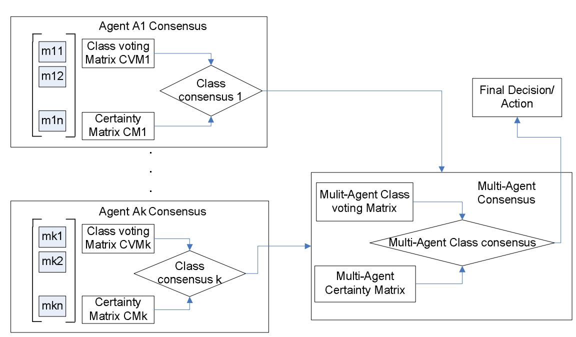


Figure 1: Block diagram of the WCCM method

2.1 Agent consensus

For those cases in which an agent consists of more than one member, an agent consensus process is done. This consensus has as objective to combine the outcome of one of more members, where each member is a classifier. The consensus process is carried out by means of a weighted voting process in which the votes of the members, represented by the Class Voting Matrixes (CVM) are weighted by certainty factors represented by the certainty matrixes (CM). These matrixes are presented by the equations (1) and (2).

$$CVM = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{1}$$

$$CM = \begin{pmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{pmatrix} \tag{2}$$

In a multi-agent environment consisting of "n" members and "m" classes to be classified, the CVM has a size mxn, where each element a_{ij}=1, with 1≤i≤m and 1≤i≤n, if the member "i" votes for the class "j" and a_{ij}=0 otherwise.

The certainty matrix consists of certainty factors which represents how accurate, truthful or reliable the classification provided by each classifier for each specific class is. The certainty matrix also has a size mxn where each element bij equals the effectiveness factors of the matrix DEDIFA presented in section 3. The outcome of the members is unified by the class consensus. For the class consensus, a numerical value called brute utility (BU) is used as a measure of the weighted outcome of each agent/member about the presence of the class i and can be calculated by the equation (3). In view that higher the number of members voting in favour to the same class, higher the level of confidence of the assessment, the utility before defined is treated as a brute utility (BU) and a net utility (NU) is obtained by multiplying BU by a coincidence factor (COF) as indicated by the equation (4), where COFi=0.5 if only one member votes in favour to the class "i", COFi=0.8 if two members votes and COFi=1 if 3 or more agents vote in favour.

$$BU_i = \sum_{k=1}^{n} CVM_{i,k} \times CM_{i,k} \tag{3}$$

$$NU = BU \times COF \tag{4}$$

As a result, from the consensus the class with the highest NU is chosen as winner class and a certainty factor (CF) is assigned to this, where the certainty values corresponds to the coincidence factors before mentioned. In case that two or more classes simultaneously fulfil the condition of highest NU, all of these classes are chosen as winners. In the field of diagnostic measurements it is important to allow two or more classes to win since in real cases it could happen that a transformer has more than one failure simultaneously. The agent class consensus process is summarized in Table 1 for multi-member agents. First, the class consensus takes place by choosing as winner the class/classes with the highest NU.

Table 1: Consensus process

Class	Member 1	Member n	Member 1	Member n	N° votes	BU	COF	NU	WINNER class	CFi
1	a_{11}	a_{1n}	b_{11}	b_{1n}	K	BU_1	CF_1	NU_1	X	CFi_1
2	a_{21}	a_{2n}	b_{21}	b_{2n}	K	BU_2	CF_2	NU_2	X	CFi_2
i	a_{i1}	a_{in}	b_{i1}	b_{in}	K	BU_i	CF_i	NU_i	X	CFi_i
m	a_{m1}	a_{mn}	b_{m1}	b_{mn}	K	BU_m	CF_m	NU_m	X	CFi_m

3 DETECTION AND DIAGNOSTIC MATRIX

The detection and diagnostic matrix of failure modes (DEDIFA) is a representation of the inter-relation among failure modes, monitoring methods and diagnostic methods. This matrix was obtained as a result of a FMEA study. An important peculiarity of DEDIFA is that the elements of this matrix corresponds to pre-defined effectiveness factors (EF) representing how effective the monitoring and diagnostic methods are against each failure mode. By default DEDIFA assigns an EF=0.9 to the diagnostic methods having a high effectiveness, an EF=0.6 to the methods having a medium effectiveness and an EF=0.4 to the methods having a low effectiveness, as shown in Figure 2. Table 2 presents the description of the abbreviations in Table 2.

4 METHODOLOGY

AICA is a multi-agent-based CA method based on the multi-state condition (MSC) model shown in Figure 3. The multi-state condition model consists in splitting the condition of a transformer during its life span into five stages as suggested in [4] and at the same time the condition at each stage is split into different states. A numerical value is assigned to each of the states for representing the condition index (CI) of the transformer at any time "t". A transformer with a CI=10 is considered as new, whereas a transformer with a CI=0 or CI=1 is considered as failed.

AICA was conceived for allowing users to set the goal of the CA to their preferences. Even when normally CA refers itself to the assessment of the overall condition of the transformer, in some cases users are only willing to assess the condition against specific failures modes. In order to fulfil this necessity, AICA allows users to select among 5 different CA goals: overall, electrical, thermal, mechanical and degradation.

	Failure modes in the active part	ON-LINE MONITORING METHODS								DIAGNOSTIC METHODS																											STAGE in the MSC model
										TRADITIONAL METHODS																			ADVANCED METHODS								
										Chemical methods										Electrical methods																	
		TWT	TOT	BOT	DGA	MORS	VIB	LRE	PD	DGA	PCEA	COND	COSU	MORS	MPED	MPIS	MPKF	FUR	DPO	TTR	EXCU	MABA	DCWR	DF/PF	INRE/POI	CGIR	SCI	IRI	FRA	FRA-SC	FRSL	FRLI	FRDF	DFTU	DRM	PD	
Electrical	Short-circuit between turns	0.6	0.6	0.6	0.9					0.4										0.9	0.6	0.6	0.4						0.6								Failed-State2, New
Electrical	Short-circuit between strands	0.6	0.6	0.6	0.9					0.4																				0.4	0.6						Failed-State2, New
Electrical	Short-circuit to ground	0.6	0.6	0.6	0.9					0.4														0.6	0.9				0.9	0.4			0.6	0.9			Failed-State2, New
Electrical	Floating potential/ungrounded core				0.9				0.9	0.4														0.4					0.9	0.9			0.4			0.9	Faulty-State2, New
Electrical	Short-circuited core laminations	0.6	0.6	0.6	0.9					0.4											0.6	0.6							0.6								Failed-State2, New
Electrical	Multiple core grounding	0.6	0.6	0.6	0.9					0.4																0.9											Faulty-State2, New
Thermal	Open-circuit failure/interrupted strands	0.6	0.6	0.6	0.9					0.4										0.6	0.4	0.4	0.9				0.4		0.9	0.9	0.6	0.4					Failed-State2, New
Thermal	Contact resistance failure	0.6	0.6	0.6	0.9					0.4													0.9					0.4	0.6	0.6							Faulty-State2, New
Mechanical	Conductor tilting/bending						0.9																						0.9	0.9							Faulty-State2, New
Mechanical	Axial instability						0.9	0.4																			0.4		0.9	0.9		0.4					Faulty-State2, New
Mechanical	Buckling						0.9	0.4																			0.6		0.9	0.9		0.6					Faulty-State2, New
Mechanical	Bulk movement						0.9	0.4																			0.6		0.9	0.9		0.6					Faulty-State2, New
Mechanical	Loose clamping structure						0.9																						0.4	0.4							Faulty-State2, New
Mechanical	Lead deformations																												0.9	0.9							Faulty-State2, New
Mechanical	Core deformation																							0.4					0.9								Faulty-State2, New
Degradation	Degradation due to water in oil					0.9					0.6	0.6		0.9										0.4	0.4								0.6	0.4	0.6		New/Normal/Defective/Faulty
Degradation	Degradation due to water in paper					0.4									0.4	0.6	0.4							0.4	0.4								0.6	0.4	0.9		New/Normal/Defective/Faulty
Degradation	Degradation due to temperature	0.9	0.9	0.6														0.4	0.4									0.4									Normal/Defective/Faulty
Degradation	Degradation due to aging by-products in oil				0.4					0.4	0.9	0.6	0.6											0.4	0.4								0.6	0.4	0.6		New/Normal/Defective/Faulty
Degradation	Degradation due to corrosive sulphur												0.9																								Faulty-State2, New
Degradation	Degradation due to aging by-products in paper				0.4					0.4								0.6	0.9					0.4	0.4								0.4	0.4			New/Normal/Defective/Faulty/Failed
Degradation	Degradation due to discharges				0.6				0.9	0.4																										0.9	Faulty-State2, New

Figure 2: Matrix DEDIFA

Table 2: Abbreviations in matrix DEDIFA

Abbre.	Description	Abbre.	Description
TWT	Winding hot spot temperature	MABA	Magnetic balance test
TOT	Top oil temperature	TTR	Ratio
BOT	Bottom oil temperature	EXCU	Exciting current
DGA	Analysis of dissolved gasses in oil	DCWR	DC winding resistance
COND	Oil conductivity	DF	Dissipation factor at rated frequency
DS	Dielectric strength	DFTU	Dissipation factor Tip-UP test
MORS	Relative saturation of moisture in oil	INRE	Insulation resistance
VIB	Vibrations	POI	Polarization index
LRE	Leakage reactance	CGIR	Core grounding insulation resistance
CGRO	Core grounding current	IRI	Infrared inspections
COSU	Corrosive sulphur analysis	FRA	Frequency response analysis
PCEA	Physical-chemical and electrical oil analysis	FRA-SC	FRA Short-circuit test
MPED	Moisture in paper based on equilibrium diagrams	FRSL	Frequency response of stray losses
MPIS	Moisture in paper based on sorption isotherms	FRDF	Frequency response of dissipation factor
MPKF	Moisture content in paper via KF titration	DRM	Dielectric response methods
FUR	Furan analysis	FRCL	Frequency response of core losses
DPO	Degree of polymerization	FRLI	Frequency response of leakage inductance
PD	Partial discharges		

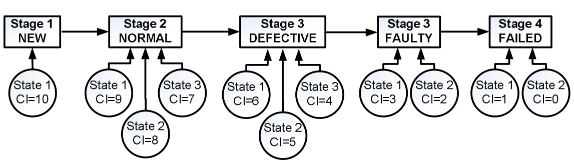


Figure 3: Multi-state condition model of AICA

The determination of a CI from data of different diagnostic methods is a complex and challenging task due to the diversity of failure modes that could take place in power transformers and due to the difficulties in combining the interpretation of results. AICA overcomes these difficulties using the WCCM method described in section 2. Figure 4 shows a block diagram of the methodology of AICA.

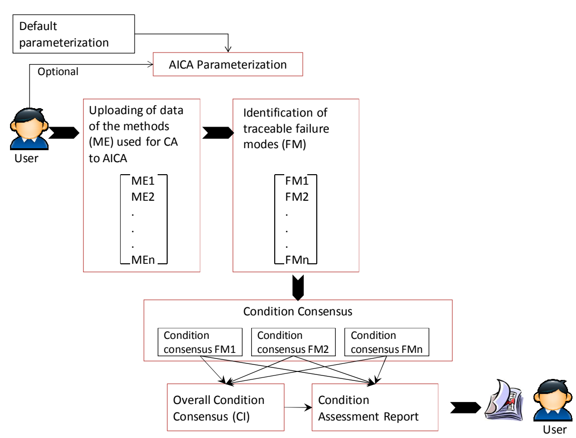


Figure 4: Block diagram of AICA

First of all, a parameterization of AICA is necessary. The parameterization consists in providing different parameters to the MSC model, to the DEFIFA matrix and to the diagnostic agents. A default parameterization of AICA is provided. However, users have the possibility of editing and modifying the parameters. This is very important because in this manner AICA has a total flexibility and can be adapted by expert-users to their preferences. After parameterization, the first action to be done by users is to upload the data of the diagnostic methods used for CA. From the uploaded data, AICA immediately identifies the failure modes that can be traced (traceable failure modes) by the diagnostic methods. Afterwards AICA performs a multi-agent condition consensus.

4.1 Condition consensus

The condition consensus consists in combining the diagnosis provided by each diagnostic agent (diagnostic method) in order to get a final consensus about the condition of a transformer. This process is done for each failure mode in an independent way (condition consensus FM1, condition consensus FM2,..., condition consensus FMn). Figure 4 illustrates the condition consensus of a hypothetical failure mode "i" using "n" diagnostic methods (ME1, ME2,..., MEn). The condition consensus combines the diagnosis provided by the diagnostic methods, which are defined in this context as agents. As also illustrated in Figure 5 for the agent 1, the agents representing the diagnostic methods are made of three elements: data of measurements (that represent the excitation of the agent from the environment), intelligence for automatic assessment and an output in the form of a stage and state in the MSC model.

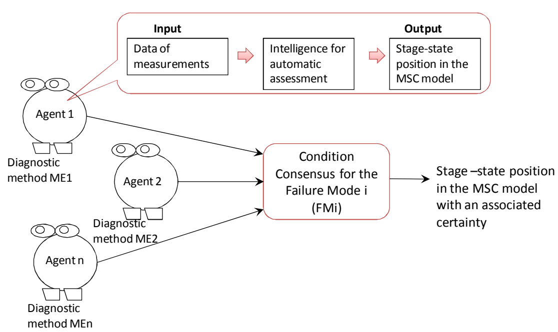


Figure 5: Condition consensus process

4.2 Overall Condition Consensus

After completing the condition consensus for each failure mode, the overall condition consensus is done as shown in Figure 4. As a result of the multi-agent consensus the overall condition of the transformer is determined and for that, the stage-state of the failure mode having the worst stage-state position in the MSC model is chosen as winner.

4.3 Condition assessment report

The CA report includes a brief overview of the nameplate data of the transformer, the goal of the assessment as well as a CI. At the same time, a certainty factor corresponding to the certainty factor CF of the winner failure mode of the overall condition consensus is provided.

The report also provides to the user an overview to the degree of completeness of the CA task. Depending on the CA goal, AICA determines the total number of traceable failure modes (TNTFM) that should be assessed. On the other hand, depending on the diagnostic methods used by the user for the CA, AICA also determines the number of failure modes assessed within the CA (NAFM). Then, the completeness of the CA is determined according to the equation 5.

$$Completeness(\%) = \frac{NAFM}{TNTFM} x100 \qquad (5)$$

5 CASE STUDY

In this section the application of AICA for CA of a 400 kV/220 kV/33 kV, 315 MVA autotransformer manufactured in 2006 is illustrated. The goal of the CA was to assess the overall condition with the aim of determining the cause of abnormal values in the DGA test shown in Table 3. For that, the following diagnostic methods were applied: oil dissipation factor, water content in oil (ppm), DGA, turns ratio, magnetic balance test, excitation current, leakage reactance, dissipation factor, DC winding resistance, frequency response of stray losses (FRSL) and frequency response analysis (FRA). The results of some of these tests are shown Figure 6.

For simplification purposes, the condition consensus process is only illustrated for the failure modes short-circuit between turns (EFST) and axial instability (MFAI) in Tables 4 and 5, respectively. On one side, according to the Table 4, all diagnostic methods able to trace the failure mode EFST indicate that the transformer is in the stage "New", that is, healthy. On the other side, Table 5 illustrates indicates that according to the method FRLI, the winding has an axial instability, thus, the transformer is in the stage "Faulty". However, according to the FRA method, from the point of the view of axial instability, the windings are in healthy condition, thus, in the stage "New". But in view that the NU value of stage "New" is higher than the NU value of the stage Faulty, the stage "New" is chose as a winner. In manner, the outcome of the FRLI and FRA were combined.

After completing the condition consensus process for all of the failure modes listed in the matrix DEDIFA, a final overall condition assessment was done as described in section 4.2. As a result, the CA report shown in Table 6 was obtained. As can be appreciated, the failure modes having the worst position in the MSC model are MFBM and DFDI. Thus, the overall condition was assessed as "Faulty" in state 2. The certainty values give an idea of the reliability of the assessment. For example, for the case of the failure MFBM, the certainty is of 0.8 (high) because two independent diagnostic methods votes in favour to this failure modes. But in contrast, the assessment of the failure DFDI is not so reliable, as the certainty is of 0.5. In summary, the transformer was assessed as faulty in state 2 and according to the MSC model, to this position a corresponds to a CI=2.

The completeness of the CA is of 90.5%. This indicates that the diagnostic method used were sufficient for assessing 90.5% of the possible failure modes that could be present in the active part.

Table 3: Results of DGA tests

Test N°	Date	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG
1	20-07-07	30	2	1	1	0	166	882	200
3	26-04-08	27	4	2	3	0	269	1372	305
4	19-07-08	26	5	2	1	0	333	1792	367
6	07-01-09	154	27	31	3	34	374	1650	623
7	16-01-09	155	25	31	5	28	421	1986	665
8	17-01-09	152	28	34	4	33	381	1620	632
9	30-01-09	140	27	30	2	24	402	1877	625

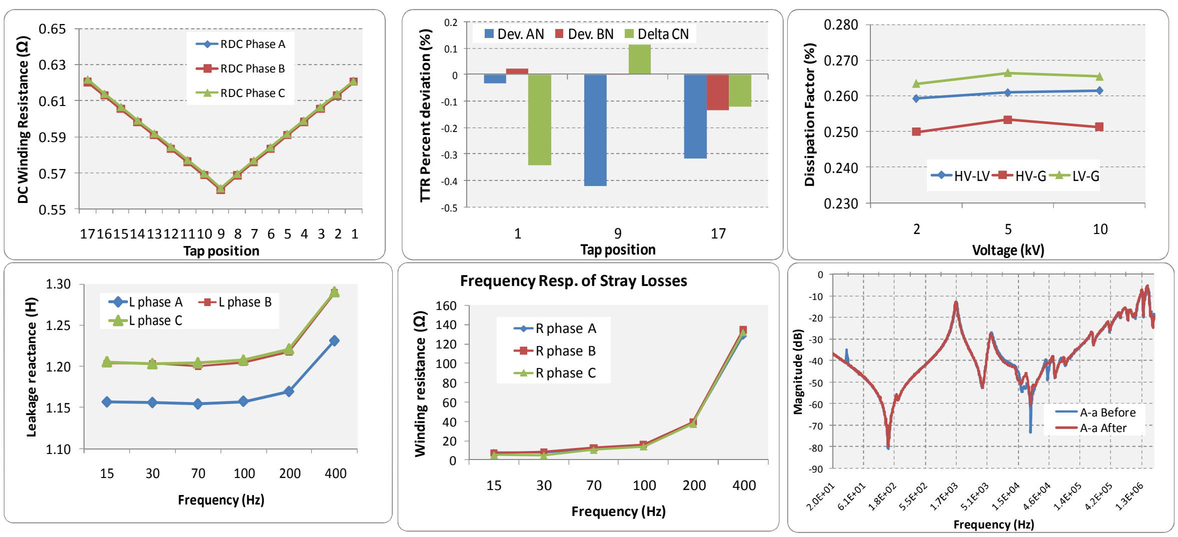


Figure 6: Results of some of the diagnostic tests applied for CA

Table 4: Condition consensus for the failure mode EFST

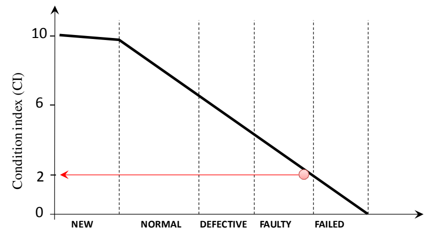
		CVM						CM						Class Consensus				
Stage	State	DGA	TTR	MABA	EXCU	DCWR	FRA	DGA	TTR	MABA	EXCU	DCWR	FRA	N° votes in favor	BU	COF	NU	Winner class
New	1	1	1	1	1	1	1	0.4	0.9	0.6	0.6	0.4	0.6	6	3.2	1.0	3.2	New
Faulty	1													0	0			
	2													0	0			

Table 5: Condition consensus for the failure modes MFAI (phase A)

		CVM		CM		Class Consensus				
Stage	State	FRLI	FRA	FRLI	FRA	N° votes in favour	BU	COF	NU	Winner class
New	1		1	0.4	0.9	1	0.9	0.5	0.45	New
Faulty	1			0.4	0.9	0	0			
	2	1		0.4	0.9	1	0.4	0.5	0.2	

Table 6: Condition assessment report

Transformer data
Serial number: 12345678, Rated Power: 315 MVA, Rated voltages 400/220 kV, Age: 4 years
Goal of the Assessment: Overall condition assessment
Overall Condition Index=2
The transformer was assessed as faulty in state 2 due to a bulk movement of a winding of the phase A and due to degradation of the insulation due to discharges.
Certainty of the assessment=0.8
Completeness=90.5%



Abbreviation	Description	MSC position	Certainty
EFST	Short-circuit between turns	New	1
EFSS	Short-circuit between strands	New	0.8
EFTG	Short-circuit to ground	New	0.8
EFFP	Floating potential	New	0.5
CFSL	Short-circuited core laminations	New	1
CFMG	Multiple core grounding	New	0.5
CFUC	Ungrounded core	New	0.5
EFOC	Open-circuit failure	New	1
EFCR	Contact resistance failure	New	1
MFCT	Conductor tilting	New	0.5
MFCB	Conductor bending	New	0.5
MFAI	Axial instability	New	0.5
MFBM	Bulk movement	Faulty, 2	0.8
MFB	Buckling	New	0.5
MFLC	Loose clamping structure	New	0.5
MFLD	Lead deformations	New	0.5
CFCD	Core deformation	New	0.5
DFWO	Degradation of insulation due to water in oil	New	0.8
DFWP	Degradation of insulation due to water in paper	Normal, 1	0.5
DFT	Degradation of insulation due to temperature	No assessed	0.5
DFAO	Degradation of insulation due to aging by-products in oil	Normal, 1	0.8
DFAP	Degradation of insulation due to aging by-products in paper	Defective, 1	0.5
DFDI	Degradation of insulation due to discharges	Faulty, 2	0.5

6 CONCLUSION

AICA is a novel method that allows transforming the results of monitoring and diagnostic measurements in a numerical value called "condition index" representing the overall condition of the active part of power transformers.

AICA is a total flexible methodology that allows expert-users to adapt it to their preferences. As default AICA uses a multi-state condition model (MSC model) which main function is to represent the condition deterioration process of a power transformer in 11 states that are grouped in 5 stages (new, normal, defective, faulty and failed). The methodology systematically identifies the diagnostic methods able to trace each failure mode by means of the matrix DEDIFA. Subsequently, each failure mode is treated as an agent having an embedded intelligence for performing automatic interpretation of results. The outcome of each agent (diagnostic method) is combined by AICA. For that, AICA uses the WCCM method for performing a condition consensus among agents for each failure mode. At the end, the failure mode having the worst stage-state position is chosen as the failure mode representing the overall condition of the transformer.

The obtained results are encouraging as the proposed method allowed to combine systematically the outcome of the diagnostic methods and as a result a numerical value called condition index representing the healthiness state of the autotransformer was obtained.

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