A Methodology for Operational Fault Diagnosis in Electrical Power Transformer: Practical Application

Abdelaziz Lakehal[1], Lotfi Saidi[2], Abdelmoumene Hechifa[3] and Arnaud Nanfak[4]

[1] Laboratory of Research on Electromechanical and Dependability, University of Souk Ahras, Souk-Ahras, Algeria
[2] Laboratory of Signal Image and Energy Mastery (SIME, LR 13ES03), Universityof Tunis, ENSIT, Tunis 1008, Tunisia
[3] LGMM Laboratory, Department of Mechanical engineering August 20, 1955, SkikdaUniversity, Skikda, Algeria
[4] Laboratory of Energy, Materials, Modelling and Methods, National Higher Polytechnic School of Douala, University of Douala, Douala, Cameroon
a.lakehal@univ-soukahras.dz

Abstract. Electrical power transformer is critical equipment in power plant and electrical power transmission and distribution. To facilitate the fault diagnosis of this electrical transformer a Bayesian network was developed and used for information fusion. 7 transformer elements were examined. 22 faults were taken care of in this study. 14 information's mainly taken from existing test and measurement equipment have been used and the main lines of their interpretations have been formulated. The main result of this contribution was a useful fault diagnosis manual for handling real problems in electrical power transformer maintenance. This contribution can help and serve as an expert decision support system for maintenance engineer. By detecting, diagnosing and decision making, the availability of electrical power transformer was improved.

Keywords: Fault diagnosis, power transformer, Bayesian network, decision making, electrical measurement.

1 Introduction

Electrical power transformers are highly critical devices that require prognostics and health management. Therefore, increasing the availability of these devices is one of the main concerns of maintenance managers. However, any predictive maintenance procedure goes through three essential steps: monitoring, diagnosis, decision-making [1].

Electrical measurement analysis is a condition-based maintenance technique for monitoring electrical transformers. It is widely used to assess the state of health of this vital and strategic equipment. The various electrical, thermal, mechanical and environmental constraints that electrical transformers are subjected to cause deviations in electrical measurements compared to standards such as IEEE C57.10.01 and IEC 60137 [2,3]. Once these values exceed limit thresholds, the transformer becomes undesirable operating conditions and the events that may appear on this equipment are feared.

To evaluate the condition of bushings and the transformer insulation, capacitance and dissipation factor measurements are taken. Aging and breaking down of insulation, or water penetration, increases the amount of energy in the form of heat in the insulation. The level of these losses is measured by the dissipation factor. Winding resistance measurements are made to diagnose winding deterioration. These measurements also make it possible to check the state of the on-load tap-changer. Also by measuring the variation of eddy currents it is possible to detect short-circuits between conductors in parallel as well as local heating.

Dissolved gas analysis represents one of the methods developed to improve the diagnosis and prediction of faults in electrical transformers. Although this method has been the subject of several codes such as: IEEE Std C57.104-2008, IEC Publication 60599 and IEC TC 10 Databases [4-6], it still has weaknesses in the prediction of faults, and the taking of decision. To make this diagnostic technique more reliable, a fusion of information from other sources appears necessary [7].

It should be underlined here that issues related to fault diagnosis and prediction of electrical power transformer has been undertaken already in the last decades. Several investigations have been carried out by researchers to improve and apply these methods in cases of specific solicitations [8]. In recent research works other methods besides traditional methods of diagnostics of electrical transformers have been developed and new precursors have been defined [9]. Although electrical transformers are static equipment, [10] Hong et al used vibration analysis as technique for monitoring and detecting their faults. Encouraging results occurred in this study, but vibration analysis also has its limitations in predicting faults.

Based on standards or modern diagnostic techniques, uncertainty still exists and decision-making remains a difficult thing. The key to making good decisions and operating transformers in a certain environment is to exploit the information held by experts. This justifies that the majority of current contributions surround themselves around information. A contribution is developed by [11] based on using a statistical notion of causal inference based on information fusion. In this work authors tried give a tool to help in the prediction of electrical behavior arising from common causal dependencies.

The information available on the device especially, that concerning the history of failures and the analysis results represents the essential elements for decision-making. The first contribution of this paper is to made a posteriori analysis method to build a prevention approach. The second one is to reconstitute a malfunction in a logical way, to seek the causes which led to the fault of the transformer element and to define the priorities in terms of corrective maintenance intervention. Through this research we will try to highlight the multi-causality of the fault, identify the most sensitive element of the transformer in order to implement preventive measures to avoid the return of an identical fault and prevent the reproduction of similar or more serious faults.

2 Condition Monitoring and Fault Diagnosis of Electrical Power Transformer

In recent years, several research works on electrical transformers have led to the definition of new diagnostic techniques. The fundamental objective is the detection of the fault and then the diagnosis of its origin. Today, improving the fault diagnosis by using artificial intelligence methods take the advantage regard to the traditional methods. To optimize decision-making, two research paths will be adopted in this paper, one concerning the classic test and measurement on the transformer and the other will be sacrificed to the information fusion from these classical methods.

The international standard IEC 60317 [3] is the reference for insulated bushings for alternating voltages above 1000 V. Aging and breaking down of insulation, or water penetration, increases the amount of energy in the form of heat in the insulation. The dissipation factor measures the level of these losses.

Ratio and excitation current measurements are made to assess possible winding deterioration by comparing ratio and measured magnetizing currents, to specifications, to factory measurement results and/or between phases. The deviation criterion of a transformation ratio greater than 0.5% from the theoretical values will be identified as faulty, and as normal if the deviation is lower [3].

Another traditional technique often used for the diagnosis of electrical transformers is the frequency response analysis. The origins of mechanical and electrical faults can be diagnosed by analyzing the frequency response. Mechanical faults can be caused by an external short circuit, for example.

Winding resistance measurements are made to assess possible deterioration of the windings. These measurements also make it possible to check the state of the on-load tap-changer. Resistance measurements are compared between the values of the three phases, or with respect to the values leaving the factory, when available.

Short circuit impedance measurements are made to assess the deterioration and possible displacement of the windings. Also, it is possible to detect short-circuits between conductors and local heating caused mainly by high losses by eddy currents.

Besides the electrical measurements, the state of the insulation is monitored by analysis of the dielectric response. This technique which makes it possible to diagnose the crossings of the active part is based on the evaluation of the water content. Also the evolution of the partial unloading in time is significant in the case of fault in the insulation of the transformers. With this type of measurement it is possible not only to determine the condition of insulating materials but also to predict their failure.

Through the methods mentioned above, information will be collected and analyzed in order to recognize the faulty state of the breast state. This information’s will be the input data in the Bayesian model developed later in this paper. Classification of faults is adopted based on the work published by the experts of the company OMICRON [12]. **Erreur ! Source du renvoi introuvable.** summarizes the faults and elements retained in this study.

Table 1. Component and Fault Types.

Transformer Component Ci	Fault Type	Code
Bushings (C1)	Partial breakdown between capacitive graded layers, cracks in resin-bonded insulation	C1F1
	Aging and moisture ingress	C1F2
	Open or compromised measuring tap connection	C1F3
	Partial discharges in insulation	C1F4
CT at bushings (C2)	Current ratio or phase error considering burden, excessive residual magnetism	C2F1
Insulation (C3)	Moisture in solid insulation	C3F1
	Aging, moisture, contamination of insulation fluids	C3F2
	Partial discharges	C3F3
Leads (C4)	Contact problems	C4F1
	Mechanical deformation	C4F2
Tap changer (C5)	Contact problems in tap selector and at diverter switch	C5F1
	Open circuit, short circuit between turns	C5F2
	Contact problems in the off-load tap-changer	C5F3
Windings (C6)	Short-circuits between windings or between turns	C6F1
	Strand-to-strand short-circuits	C6F2
	Open circuits in parallel strands	C6F3
	Short-circuit to ground	C6F4
	Mechanical deformation	C6F5
	Contact problems, open circuits	C6F6
Core (C7)	Mechanical deformation	C7F1
	Floating core ground	C7F2
	Shorted core laminates	C7F3

3 Bayesian Theory

Bayesian theory includes graph theory and probability theory. The Bayesian reasoning is modeled by a network which consists of two elements which are: the structure and the parameters. The structure is defined and optimized by graph theory, while the parameters are given by probability theory. Directed Acyclic Graph represents the structure of the Bayesian network as shown in **Erreur ! Source du renvoi introuvable.**. The learning of the parameters and the structure allows a better Bayesian modeling. One of the oldest applications of Bayesian inference is decision making [13]. Other researcher used Bayesian reasoning for diagnosis, prediction, reliability and others [14]. Inference using Bayes' theorem makes it possible to update the likelihood of a hypothesis based on a previous estimate of this likelihood and new information.

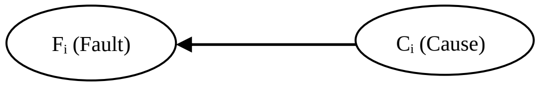

Fig.1. Simple BN for fault diagnosis.

For example, for diagnostic issues, let events C and F such that C is the cause and F represents the consequence (fault). Bayes' theorem makes it possible to determine the probability of existence of the fault C knowing F, if we know the probabilities of C, B and F knowing C, provided that the probability of F is not equal to 0.

The Bayesian theory is given by:

$$P(C|F) = \frac{P(F|C)P(C)}{P(F)} \quad (1)$$

Inference in Bayesian network is to update probabilities. In this study by using the same model we can make fault diagnosis (causes→symptoms), or fault prediction (symptoms→causes).

The basis of Bayesian computing is probabilistic inference. This Bayesian inference has several advantages over other artificial intelligence methods such as neural networks and decision trees. Variables are defined as in the other techniques of artificial intelligence while this is not the case for their role. Another advantage is that inference is possible in all directions. For the problem addressed in this paper, it is possible to make inference for diagnosis and prediction from the same model. Bayesian inference is mainly based on the probability tables of the nodes which represent the parameters of the Bayesian network (variables of the model) and the arcs which represent the conditional independences (structure of the network).

The application of Bayesian networks in the field of industrial diagnostics has given promising results [15]. The same applies to the diagnosis and prediction of faults in electrical transformers based on the analysis of gases dissolved in oil [16]. The contribution that Bayesian networks give alongside other artificial intelligence techniques to traditional diagnostic methods is very significant [16].

4 Practical Application and Results

In this section, practical application of the proposed method is made for fault diagnosis of an electrical transformer of a power plant of the Algerian Company of Electricity Production, SONELGAZ/SPE. Analyses were performed on a step-down transformer (15.5 / 6.6kV) with a power of 20 MVA (**Erreur ! Source du renvoi introuvable.**).

Fig.2. The studied electrical power transformer.

The major operational problems in the case study of the electrical power transformer endanger its seven main elements which are: Bushings, CT at bushings, Insulation, Leads, Tap changer, Windings, Core (**Erreur ! Source du renvoi introuvable.**). In this application, the choice of these elements is strongly related to the existing test and measurement equipment, but the methodology can be extended to other elements if the related information exists.

Usually, the operational problems of an electrical power transformer are not easily detected and need very developed instrument, and on the basis of the information given by these instruments it's possible to identify the causes of each problem. To achieve a good solution for each problem, its actual causes must be faced. Unfortunately, the diagnosis task is very difficult in the case where some faults occur together. Also, a fault that is not detected in time or detected late can cause the failure of other elements of the electrical transformer.

Another problem is the lack of know-how and experience among the maintenance engineers force them to face any problem by applying temporary measures that postpone and displace it to another service or another job in the power plant. The solution is the use of a computer program and the recording of information from the measuring devices and feedback experience in these programs. The Bayesian network which will be developed in this section represents a decision-making aid tool for the diagnosis of electrical transformer faults.

The task of fault diagnosis is extremely difficult because the problem’s symptom–cause relationship is not a unique direct link. It is possible for one fault to have several causes and one cause to result in more than one problem. Also, a cause could be the cause the breakdown of one element of the transformer and at the same time has an impact on other elements.

Now, based on feedback and the experience of operators and maintainers, each cause has a probability and each defect has these causes. The network of **Erreur ! Source du renvoi introuvable.** represents the structure of the Bayesian network which makes it possible to diagnose the faults of Insulation. The variables are discrete but there are some cases where it’s possible to use continuous variables to model the fault diagnosis of electrical power transformer, for example in the case of dissolved gas analysis variables.

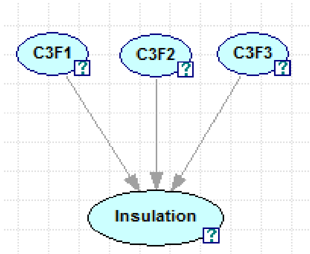

Fig.3. BN for Insulation fault diagnosis.

The Conditional Probability Table (CPT) quantifies the causalities in the Bayesian reasoning presented above. **Erreur ! Source du renvoi introuvable.** presents the links between the three faults that can cause transformer insulation breakdown. Each variable in the network of the **Erreur ! Source du renvoi introuvable.** can take two states: True (T) and False (F). In this case study the variables are discrete. However, it should be noted that Bayesian networks offer modeling possibilities with continuous variables.

Table 2. Table captions should be placed above the tables.

	C3F1	True				True			
	C3F2	True		False		True		False	
	C3F3	T	F	T	F	T	F	T	F
Insulation	True	1	1	1	1	1	1	1	0
	False	0	0	0	0	0	0	0	1

From the CPT of **Erreur ! Source du renvoi introuvable.** it is possible to do some reading as follows:

- If one of the causes C3F1, C3F2 and C3F3 occurs then the Insulation breakdowns.
- If it will not take place for the four causes then the insulation is safety.

To make a diagnosis and make certain decisions based on the Bayesian theory, it is necessary to calculate the probability that an element of the transformer breaks down knowing that it is not broken down immediately. You have to be careful with the terms here, because faulty element means the transformer fails immediately, partially faulty means it fails after a few hours, so not immediately, and acceptable means it does not fail.

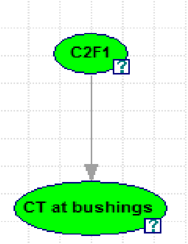

Fig.4. BN for CT at bushings fault diagnosis.

In **Erreur ! Source du renvoi introuvable.** the causality is strict which means that any new information on the C2F1 variable changes the beliefs of the modeler and the probability that the CT at bushings fault appears is 100% (evidence).

Erreur ! Source du renvoi introuvable. 6, 7, 8 and 9 successively represent the Bayesian networks of faults in Bushings, Leads, Tap changer, Windings and Core of the electrical power transformer.

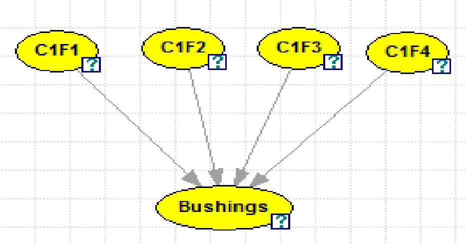

Fig.5. BN for Bushings fault diagnosis.

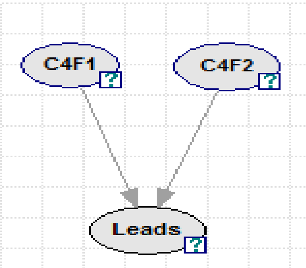

Fig.6. BN for Leads.

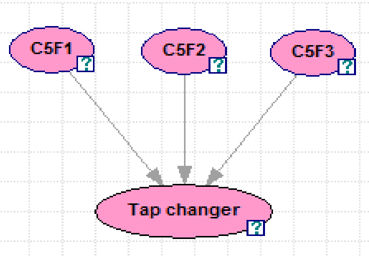

Fig.7. BN for Tap changer fault diagnosis.

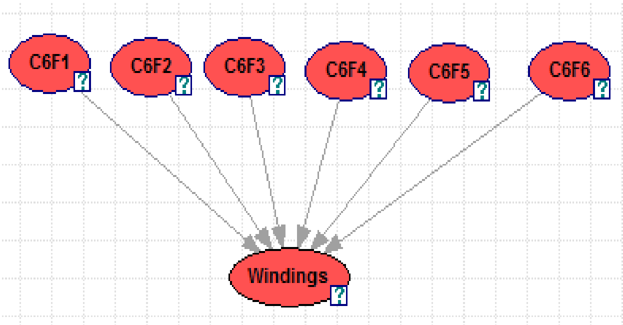

Fig.8. BN for Windings fault diagnosis.

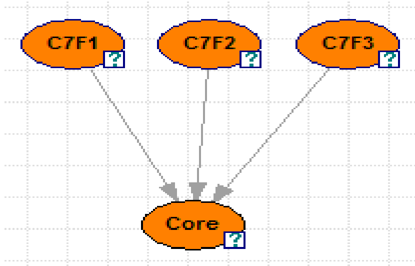

Fig.9. BN for Core fault diagnosis.

Referring to the history file of the studied electrical power transformer, the results of the conducted diagnostics, it's possible to define the a priori probabilities for each cause (**Erreur ! Source du renvoi introuvable.**). From 45 faults each cause is defined by a probability as given by **Erreur ! Source du renvoi introuvable.**. By using the CPT and the Bayesian theorem it is possible to calculate the a posteriori probabilities.

Table 2. The Parameters of the Developed BN Befor and After Inference.

Transformer Component Ci	Code	A priori probabilities	A posteriori probabilities
Bushings (C1)	C1F1	0.0444	0.4755
	C1F2	01333	
	C1F3	0.0222	
	C1F4	0.0222	
CT at bushings (C2)	C2F1	0.0222	0.0222
Insulation (C3)	C3F1	0.1333	0.2467
	C3F2	0.1111	
	C3F3	0.0222	
Leads (C4)	C4F1	0.0222	0.0439
	C4F2	0.0222	
Tap changer (C5)	C5F1	0.0222	0.0864
	C5F2	0.0444	

	C5F3	0.0222	
Windings (C6)	C6F1	0.0222	0.2403
	C6F2	0.0667	
	C6F3	0.0222	
	C6F4	0.0444	
	C6F5	0.0888	
	C6F6	0.0222	
Core (C7)	C7F1	0.0444	0.0864
	C7F2	0.0222	
	C7F3	0.0222	

From the results of the inference presented in Table 3, it is possible to define the monitoring operations of the electrical power transformer which, within the framework of systematic preventive maintenance, take place according to a determined periodicity. It is also necessary to increase the frequency of inspections for the following transformer elements: Bushings (C1), Insulation (C3) and Windings (C6). These interventions correspond to a list of operations defined beforehand which can lead to the dismantling of components and immobilization of equipment. The results shown in Table 3 can be used to anticipate transformer failures. The information used is gathered and merged into the same model.

The results found are specific to the transformer studied in this paper because they depend on the a priori probabilities. Whereas developed Bayesian networks are standard and valid for any other power transformer. In conclusion, if the parameters of the networks change from one study to another, the structure remains the same.

5 Conclusion

Despite the fact that the objective of preventive maintenance is to reduce the transformer failure rate, preventive maintenance is expensive and is not infallible. It therefore becomes legitimate to implement a preventive maintenance policy for the most critical elements of the transformer and then to choose an exclusively corrective policy for the only equipment whose criticality is minor or even zero and this well according to the financial resources. The Bayesian networks presented and used in this paper show the interest and the advantage that can bring in fault diagnosis and the decision making with regard to the actions of electrical power transformer maintenance.

The main objective of a decision statement is to allow a good selection of solutions. In this study a multi-information fusion model was proposed to define the transformer components that have a high priority. Consequently, deciding is knows the cause which will help us come up with a better action of predictive maintenance. Future work will focus on the multisource information fusion. The method will studied the fault prediction of electrical power transformer. The stability, the accuracy and the sensitivity will be examined.

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