

MONITORING AND DIAGNOSIS METHODS FOR HIGH VOLTAGE POWER TRANSFORMERS

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Transformatoarele de putere de înaltă tensiune reprezintă unele din cele mai costisitoare echipamente din stațiile electrice din sistemul electroenergetic. Defectele și opririle accidentale ale acestora nu cauzează numai costuri cu reparațiile; ele conduc și la pierderi economice datorate întreruperii alimentării consumatorilor. Testele preventive și monitorizarea on-line sunt benefice pentru prezicerea condițiilor incipiente ale defectelor și pentru stabilirea/programarea acțiunilor de mentenanță și de retrageri din exploatare/inlocuire. De aceea, în lucrare, s-a realizat o sinteză a posibilităților de monitorizare on-line și a sistemelor de detecție și diagnoză a defectelor pentru menținerea parametrilor optimi de funcționare și a unei disponibilități mărite pentru transformatoarele de putere existente.

One of the most costly equipment in electrical power systems are the High Voltage Power Transformers (HVPT). Faults and failures for these equipments does not only cause repair cost, furthermore economic losses occur due to interruptions in consumers' energy supply. Preventive tests and on-line monitoring are used to predict incipient fault conditions, and to schedule outage maintenance and retirement of the transformers. This paper presents a survey on various approaches on monitoring and fault detection of electrical power transformers used to optimize maintenance techniques. This optimization is not possible without a correct fault diagnosis besides critical components and common failure modes knowledge.

Keywords: high voltage power transformer monitoring, fault detection and diagnosis methods, maintenance.

1. Introduction

During the last years some newer maintenance strategies as predictive maintenance or reability centred maintenance got more common as more diagnostic and monitoring technologies were available on the market.

Many new devices have been developed to help in providing information that can be used in diagnosing the health of transformers. There are many key

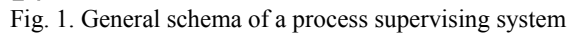
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- strict monitoring during entire transformer life cycle;
- performing diagnosis methods;
- maintenance advices recommendations.

Within automatic control of technical systems, supervisory functions serve to detect undesired or unpermitted process states and take appropriate actions in order to maintain the operation and to avoid damages or accidents [3]. In Fig. 1 is presented a general schema of process supervising system with fault diagnosis[4].



The first level of the supervising system is represented by data acquisition and automatic control function. Monitoring function assures measured signal checking with regards to the tolerance and alarms are generated for the operators. In the case of a dangerous process state, the automatic protection function starts an appropriate counteraction. Supervision with fault diagnosis is based on measured variables. Based on these variables, features are calculated and symptoms are generated via change detection. If a fault has occurred the fault

type, size and location must be identified. A fault diagnosis consists in determining these characteristics of a fault. There are several different methods to use the monitoring data and deduce useful information about the health of the transformer. One method is to use analytical modelling and another one is to use artificial intelligence techniques to identify the system, observe them, and detect faults in the system once undesired patterns are observed. These patterns are obtained using the expertise of individuals who have worked with transformers to determine thresholds for making decisions based on different sensor values.

The monitoring signals and sensors and the most commonly accepted thresholds used in transformer diagnostics are given in the following section 3.

3. Power Transformer Monitoring Systems

High Voltage Power Transformers (HVPT) monitoring systems includes specific measurements regarding: the water in oil, combustible gas in oil, temperature, gas pressure, insulation properties, partial discharge, acoustic signatures, motor current profiles, bushing leakage current detection, moisture in insulation, spectral content of shell vibration, and load current and voltage [6].

An overview of monitoring techniques used to evaluate the transformer functioning based on specific measurements is given below.

The first considered technique is the ***Dissolved gas analysis (DGA)***. When various faults develop, it is known that different gases are generated. By taking samples of the mineral oil inside a transformer, one can determine what gases are present and their concentration levels. In [7] Halstead proved that there is a relationship between fault temperature and the composition of the gases dissolved in oil (Fig. 2). Much effort has been made into creating diagnosis criteria for the types and amounts of gases that are present in the oil [8]. Some studies have focused on key gases and what faults they could identify [9]. A summary of the relationship between fault types and the key gases is given in Table 1.

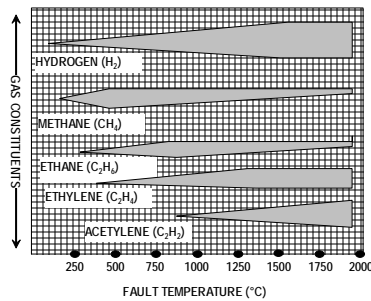


Fig. 2. Gases generated during breakdown of dielectric oil

Table 1.

Key gases for DGA and their fault type

Key Gas	Chemical Symbol	Fault Type
Hydrogen	H ₂	Electrical Corona
Carbon Monoxide and Carbon Dioxide	CO CO ₂	Cellulose insulation Breakdown
Methane and Ethane	CH ₄ C ₂ H ₆	Low temperature Oil breakdown
Acetylene	C ₂ H ₂	Electrical Arcing
Ethylene	C ₂ H ₄	High temperature oil breakdown

Moisture Analysis. *Water in the oil* indicates paper aging, since the cellulose insulation used in power transformers is known to produce water when it degrades [10]. *Water and oxygen* in the mineral oil further increases the rate at which the insulation will degrade (and Fig. 4).

A fuzzy-logic identification tool was used to detect the water-in-paper activity. On-line measurements of the water saturation in the oil, top and bottom oil temperatures, and load are used to determine this activity [11].

The limit criterion for moisture content is almost universally used to indicate insulation deterioration, oil leaks, and overheating of the transformer.

Partial Discharge Monitoring. Most incipient dielectric failures will generate numerous partial discharges before the catastrophic electrical failure. The measurement of partial discharges is probably the most effective method to detect pending failure in the electrical system. During discharges, ultrahigh frequency waves are emitted. Partial discharges may occur only right before failure but may also be present for years before any type of failure. A high occurrence of partial discharges can indicate voids, cracking, contamination or abnormal electrical stress in the insulation [10].

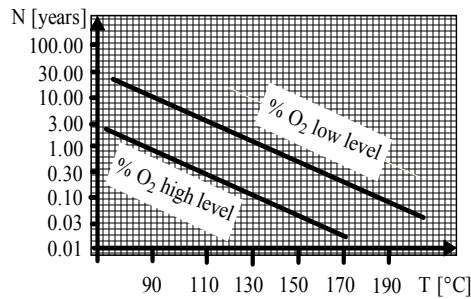


Fig. 3. Relation between the insulation's life cycle, %O₂ and operating temperature

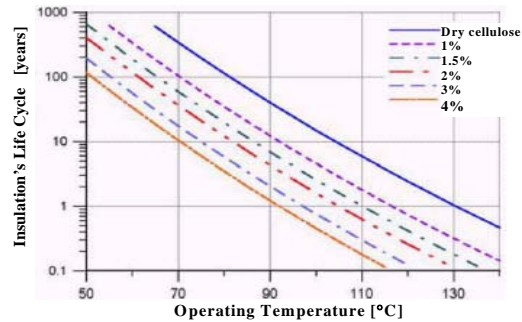


Fig. 4. Relation between the insulation's life cycle, water and operating temperature

At first, techniques to be able to detect partial discharges were few and far between. Luckily, because of the ultra-high frequency (UHF) waves produced during partial discharge, sensors have been developed that use UHF couplers to detect frequencies from 300-1500 MHz [12]. The advantage of partial discharge sensors is the ability to detect the actual location of insulation deterioration, unlike with dissolved gas sensors.

Temperature Monitoring. Abnormal temperature readings almost always indicate some type of failure in a transformer. For this reason, it has become common practice to monitor the hot spot, main tank, and bottom tank temperatures on the shell of a transformer. Monitoring the temperature of the load

tap changer (LTC) is critical in determining if this one would fail. In addition to the LTC, abnormal temperatures in the bushings, pumps, and fans can all be signs of impending failures.

The *thermography* technique is used to detect temperature gradients on external surfaces of the transformer [13]. In order to make on-line monitoring possible, thermocouples are placed externally on the transformer and provide real-time data on the temperature at various locations on the transformer. High main tank temperatures have been known to indicate oil deterioration, insulation degradation, and water formation (Kirtley, 1996).

Vibration Monitoring. This diagnostic methods is used to detect a failure in electrical insulation around the coils. Studies of transformer breakdowns have shown that between 70 and 80% of failures are caused by a short circuit between turns. While the frequency spectra of the vibration often proves more valuable information, excessive vibrations on the shell of a transformer can often be an indication of some malfunction of the transformer. The pumps or fans may no longer be operating properly. The coils or magnetic core may have been jarred loose. All of these malfunctions may ultimately lead to a transformer failure.

Current Monitoring. This diagnostic tools have been developed recently for monitoring the currents on the primary, secondary, and tertiary coils [6]. In addition, monitoring the current being drawn by the fans and pumps can also indicate when there might be a failure in these accessory units. Monitoring these currents may often be an easier and cheaper alternative than thermography or other types of thermal monitoring. It is important to monitor the appropriate operation of the cooling system.

Bushing, Current Transformers and Load Tap Changers Monitoring. The life of a transformer is predominantly shortened by the deterioration of its accessories (the bushings, load tap changers, and cooling system).

Nearly 50% of defects are from these accessories, while only 20% are from the failure of the insulation system [14]. More notably, 70% of transformers have revealed problems with the bushings.

Some of the causes of bushing failures include changing dielectric properties with age, oil leaks, design or manufacturing flaws, or the presence of moisture. Similar to the insulation around the transformer coils, there are also layers of foil and oil impregnated insulation that surround the transformer bushings and current transformers. There is a small amount of charging current that flows when the system is running. Changes in this charging current can indicate degradation in the insulation.

Overheated the load tap changers (LTCs) can result from many different phenomena. Though the contact temperature cannot easily be measured directly, the overheating will generally result in an increase in the LTC oil temperature. Therefore, wear in an LTC can be detected by monitoring the temperature

differential between the oil of the load tap changer and the oil of the main tank. By monitoring the LTC temperature closely, the flashover between the contacts can be avoided, which usually results in a short circuit of the regulating winding and subsequent failure of the transformer.

4. Transformer Modelling for Fault Detection and Diagnosis

Many different methods for detection of an impending failure in a system have been developed. These methods can be classified into two main categories:

- *analytic model-based approach* to fault detection. In this case, linear or nonlinear system theory is used to develop system models. The model can represent electrical, mechanical, thermal, or hybrid dynamics that take place in the system. These analytic models attempt to represent the system by mathematical expressions. From these models, fault detection may be achieved analytically by comparing the model's reconstructed and estimated measurements with the actual behaviour of the system, depicted by available sensor measurements. Model-based monitoring of transformers was introduced by MIT researchers [15].
- *knowledge-based approach*. From the human knowledge, rules are formed and decisions are made based on the rules. This method can utilize artificial intelligence for automatic generation of the rules and making decision [16, 17, 18].

If analytic evaluation of the residuals, in the analytic model based approach, is not suitable, fault detection may be made by an expert system based on heuristic rules. In this case, the final fault decision will be made by the human operator, as might be the case with the knowledge-based approach as well.

The transformer system is very complex. Basically the construction of a HV power transformer is modelled by sub-systems as in Fig. 5.

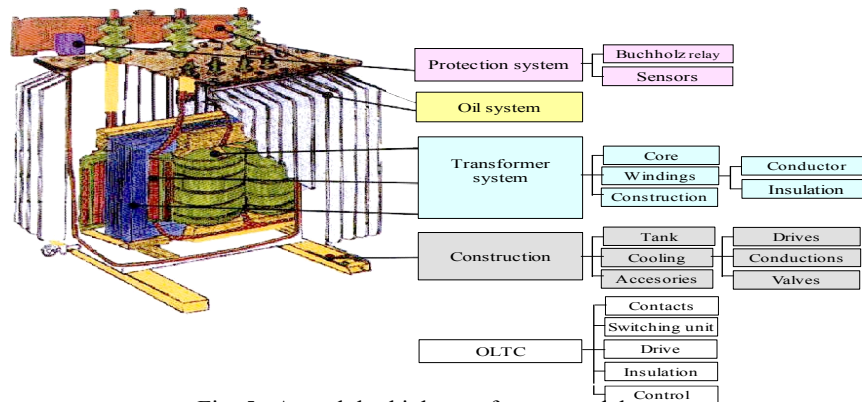


Fig. 5. A modular high transformer model

Fault descriptions could be assigned to various functional groups of the model considering the components of the transformer affected by faults.

4.1. Analytic Model-based Approach

From the physical point of view it contains thermal, mechanical, electrical, and fluid systems. Though most effort was made at linear models of the transformer systems, it quickly became evident that non-linear models provided for more accurate system identification [19]. Many different types of models have been developed to try to identify the system and detect failures. Using these models, it has become possible to detect faults by noticing abrupt and slowly developing changes in the model parameters. The added complexity that non-linearity introduces to system modelling renders it impractical in most cases.

The most common models that have been experimented with are *thermal models* [13, 20, 21, 22, 23].

On the mechanical side, a mathematical model has been derived to express the mechanical stresses due to forces on the transformer windings. This model provides critical information on the possible damage that is caused from radial short-circuit forces and gives an assessment of the possibility that a catastrophic fault from a winding short circuit could occur [24]. Diagnostics of the *electrical system* have been developed using *the transfer function method* [25].

In addition to the mechanical and electrical modelling strategies, *fluid models* have been developed for the transformer oil and its gas content. The model indicates the temperature levels at which the bubbles form and thus allows for warnings when the temperature reaches the levels indicated by the model [26]. Finally, *chemical models* of the transformer insulation have also been developed. The insulation model uses degree of polymerization and tensile strength of the insulation to make fairly accurate estimations of the aging and life expectancy of the insulation [27]. The thermal models and many of the others given above are based in the time domain.

In the past few years, *identification based models* of power transformer have been formed from frequency response data [28]. In this study, transformers are identified through the use of a subspace-based algorithm in coordination with non-linear least squares technique. The identified transformers have a dynamic range of 1 MHz and still produce accurate models. In this method, mathematical frequency-based models are formed from which equivalent circuits can be derived to match the frequency response of the model. The resulting models are usually higher order but can be reduced through model reduction and still produce highly accurate mathematical representations of the system.

4.2. Knowledge-based Approach

The modelling techniques described above require significant knowledge about the system. The physics behind the operation of the transformer has to be derived. This type of modelling is known as **white box modelling**. For the model to be successful there must be information available about the inner operation of the system. On the other side of the spectrum, there is black box modelling (Fig.6) that does not require knowledge of the inner operation of the system. Artificial intelligence is the classic example of the black box mode and it trains itself the system providing diagnostic information based on a set of inputs and outputs.

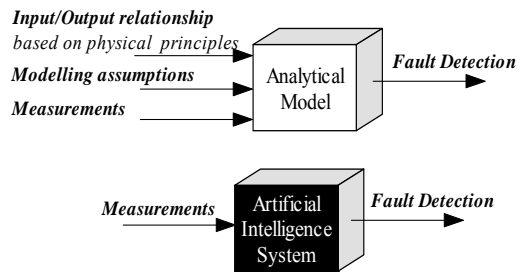


Fig. 6. Comparison between white and black box diagnostics

The non-linearity of transformers makes it exceedingly difficult to create white box models that provide a high level of accuracy. In addition, the many subsystems (thermal, mechanical, electrical, fluid) present in a transformer make the system modelling very complex. Therefore, a feasible solution is the black box modelling, centred around various artificial intelligence techniques [16, 17, 18]. The artificial intelligence can solely be used or a hybrid of knowledge-based and model-based techniques can be used (grey box diagnosis).

6. Conclusion

Transformer diagnosis is an expanding field of study. This diagnosis must consider information delivered by the manufacturer, information relating to the conditions of dissolved gas in the transformer, transformers size, volume of oil, gassing rates, loading history and environmental factors and also on-line information about dissolved gases, moisture content, partial discharges, temperature, vibration and current monitoring. The historic diagnosis records are important in future similar case diagnosis.

Modern model based fault detection techniques can, in principle, be applied to any system to provide continuous and unambiguous indication of the condition of the system.

Intelligent systems as expert system, fuzzy techniques or artificial neural networks has been also used for diagnose different faults of transformers. Expert

systems are programmed according to “expert” knowledge regarding fault condition evidence, and used thresholds from the sensors to determinate the evidence of a fault. In order to complete knowledge requirements of an expert system, much research has been done on data analysis through more analytical and artificial intelligence techniques. These techniques are used to identify the transformer dynamics and detect failures from this identification. Many different methods have been tried, some with more success than others.

The diagnosis approaches developed by different research teams can be divided into several parts. First relevant diagnostic data must be collected from the sensors and historic diagnosis and operation data from the experts. From the measurements some are chosen to be either inputs or outputs. Then the appropriate implemented technique is used to estimate the outputs from the inputs. These estimations are compared to the measured outputs and residual values are obtained. If the residual values are greater than a thresholds limit than the appearance of a fault is announced. The second step is to analyze the residuals values in order to diagnose the occurred failure. The assessment of the transformer health and any need for maintenance can be established.

REFERENCES

- [1] *Costinas, S.* (2005) *Principiile si managementul mentenantei statiilor electrice*, Ed. Printech, București.
- [2] *Comanescu, Gh., Costinas, S., Iordache, M.* (2005) *Partea Electrica a centralelor si statiilor*, Ed. Printech, Bucuresti.
- [3] *Mihoc, D., Iliescu, S.St.* (1983). *Automatizari si protectii prin relee in sistemele electroenergetice*, Editura Didactica si Pedagogica, Bucuresti
- [4] *Făgărășan, I.* (2004) *Metode de detectare a defectelor utilizand modele analitice*, ISBN 973-718-144-1, Editura Printech, București.
- [5] *Isermann, R., Balle, P.* (1997) Trends in the application of model-based fault detection and diagnosis of technical processes. *Control Engineering Practice*, Vol. 5, pp. 707-719.
- [6] *Farquharson, R.* (2000). Integrated Substation Control and equipment Monitoring and Diagnostics-An Overview. In: *Proceedings of the CEPsi 2000 Conference*. Manila, Philippines.
- [7] *Halstead, W.D.* (1973). A Thermodynamic Assessment of the Formation of Gaseous Hydrocarbons in Faulty Transformers. *Journal of the Institute of Petroleum*, **59**, pp. 239-241.
- [8] *Zhang, Y., Ding, X., Liu, Y., and Griffin, P.J.* 1996. An Artificial Neural Network Approach to Transformer Fault Diagnosis. *IEEE Transactions on Power Delivery*, **11**(4), pp.1836-1841.
- [9] *Griffin, P.J.* (1988). Criteria for Interpretation of Data for Dissolved Gases in Oil Transformers (A Review). *Electrical Insulating Oils*, STP998. American Society for Testing and Materials, Philadelphia, pp 89-106.
- [10] *Ward, B.* (2001). A survey of New Techniques in Insulation Monitoring of Power Transformers. *IEEE Electrical Insulation Magazine*, **17**(3), pp 16-23.
- [11] *Davydov, V.* (1998). Evaluation of Water Content in Transformer Insulation Systems. In: *Proceedings of Substation Equipment Diagnostics Conference VI*. TR-11131.

- [12] Judd, M.D., Pryor, B.M., Farish, O., Pearson, J.S., and Breckenridge, T. (2000). Power Transformer Monitoring Using UHF Sensors. IEEE International Symposium on Electrical Insulation. Anaheim, CA.
- [13] Kirtley Jr., J.L., Hagman, W.H., Lesieutre, B.C., Boyd, M.J., Warren, E.P., Chou, H.P., and Tabors, R.D. (1996). Monitoring the Health of Transformers. IEEE Computer Applications of Power, **63**, pp.18-23.
- [14] Sokolov, V., Bulgakova, V., and Berler, Z. 2001. Assessment of Power Transformer Insulation Condition. Pages 605-613 of: Proceedings Electrical Insulation Conference and Electrical Manufacturing & Coil Winding Conference, 2001.
- [15] Hagman, W.H., Kirtley Jr., J.L., Lesieutre, B.C., Boyd, M.J., Warren, E.P., Chou, H.P., and Tabors, R.D. (1996). Model-based Monitoring of Transformers. Massachusetts Institute of Technology, Laboratory for Electromagnetic and Electronic Systems. <http://power.mit.edu/transformer/paper.html>, (Jan.).
- [16] Roizman, O. and Davydov, V. (2000). Neuro-fuzzy Algorithms for Power Transformer Diagnostics. In: Proceedings of the International Conference on Power System Technology, 2000. Perth, WA, Australia.
- [17] Szczepaniak, P.S. (2001). Fuzzy and Genetic Approach to Diagnosis of Power Transformers. Pages 417-422 of: Proceedings volume from the 4th IFAC Symposium on Fault Detection, Supervision, and Safety for Technical Processes 2000, vol. 2.
- [18] Wang, J. and Ji, Y. (2002). Application of Petri Nets in Transformer Fault Diagnosis. Power System Technology, **26**(8), pp. 21-24.
- [19] Archer, W.E., Deveney, M.F., and Nagel, R.L. (1994). Non-linear Transformer Modeling and Simulation. Midwest Symposium on Circuits and Systems, **1**, pp. 665-669.
- [20] Lesieutre, B.C., Hagman, W.H., and Kirtley Jr., J.L. (1997). Improved Transformer Top Oil Temperature Model for Use in an On-line Monitoring and Diagnostic System. IEEE Transactions on Power Delivery, **12**(1), pp. 249-256.
- [21] Ottele, S.A. 1999. Parameter Estimator and Observer Design for Power Transformer Diagnostics. M.Phil. thesis, Colorado School of Mines, Engineering Department.
- [22] Zocholl, S.E. and Guzman, A. 1999. Thermal Models in Power System Protection. In: Proceedings of the 26th Annual Western Protective Relay Conference. Spokane, Washington.
- [23] Meliopoulos, A.P.S. (2001). State Estimation Methods Applied to Transformer Monitoring. Pages 419-423 of: Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference, 1. Vancouver, BC, Canada.
- [24] Weselucha, Z. 1995. Mathematical Model of Mechanical Stresses due to Radial Short-Circuit Forces of the Transformer Windings. In: Proceedings of the Chinese International Conference of Electrical Machines. Hangzhou, China.
- [25] Christian, J., Feser, K., Sundermann, U., and Leibfried, T. (1999). Diagnostics of Power Transformers by Using the Transfer Function Method. In: Proceedings of the 11th International Symposium on High Voltage Engineering. London, United Kingdom.
- [26] McNutt, W.J., Rouse, T.O., and Kaufmann, G.H. (1995). Mathematical Modeling of Bubble Evolution in Transformers. IEEE Transactions on Power Apparatus and Systems, **PAS-104**(2), pp. 477-487.
- [27] Pansuwan, S., Sen, P.K., and Nelson, J.P. (2000). Overloading, Loss-of-life and Assessment of Remaining Life Expectancy of Oil-cooled Transformers. Pages 143-149 of: Proceedings of American Power Conference, 62.
- [28] Akcay, H., Islam, S., and Ninness, Brett. (1999). Subspace-based Identification of Power Transformer Models from Frequency Response Data. IEEE Transactions on Instrumentation and Measurement, **48**(3), pp. 700-704.