TATA CONSULTANCY SERVICES

Experience certainty. IT Services
Business Solutions
Outsourcing

Fault Diagnosis – Isolation of Malfunctions in Power Transformers

10/06/2009

Abstract

Power transformers are designed to transmit and distribute electrical power. Depending on the size of a transformer, replacement costs can range from a few hundred dollars to millions of dollars. Performing offline and invasive tests also add to the replacement cost. Hence, there is an increasing need to move from traditional schedule-based maintenance programs to condition-based maintenance. A large number of techniques are available for transformer health monitoring. However, a focused approach is required for diagnostics. Considering the long service life of a power transformer and prevalent use of human judgment (expert), there is a need to structure a knowledge base around expert knowledge while continuing to create new diagnostic capabilities which can be plugged in. This paper gives an overview about how fusion of appropriate Artificial Intelligence-based techniques can be used in diagnostics of power transformers.

About the Authors

Jessy G. Smith

Jessy is a Senior Researcher in EIS-Innovation Labs with 7 years of experience in data based modeling, controls and diagnostics.

B Venkoba Rao

Venkoba Rao is a Scientist in EIS-Innovation Labs. He has worked extensively on process modeling and data based approaches. He has more than 11 years of experience in research.

Vivek Diwanji

Vivek is a Lead Researcher in Engineering Industrial Services (EIS)-Innovation Labs. He has overall experience of 12 years in the area of data analytics, modeling, simulation and control system design.

Shivaram Kamat

Shivaram is a key member of the Embedded Technology Center of Excellence for 'New Product Development' initiative under EIS. He has total experience of 18 years in the area of data analytics, modeling, simulation and control system and diagnostics

Contents

Introduction

Reliable and continued performance of power transformers is the key to profitable generation and transmission of electric power. Their cost of acquisition, replacement, transportation, installation and repairs are among the highest. Therefore failure results in unavailability of equipment and loss of revenue. Catastrophic failures result in substantial costs towards peripheral equipment destruction, environmental damage, unplanned utilization of human resources, and alternative power sources. Typical causes include external factors such as lightning strikes, system overload, short circuit and internal factors such as insulation deterioration, loss of winding clamping, overheating, presence of oxygen, moisture, and solids in the insulating oil.

A number of standards have evolved with time on transformer loading and transformer diagnostics to minimize unplanned outages. For example, Dissolved Gas Analysis (DGA) is a technique used to assess incipient faults of the transformer by analyzing ratios of specific dissolved gas concentrations arising from the deterioration of the transformer insulation. DGA interpretation uses methods such as IEC / IEEE standard, Roger's ratio, Duval triangle, etc. [1]. However, there is still no universally accepted interpretation technique for these tests and 'expert opinion' is often sought when any damaging trend is observed as a result of DGA techniques.

Generally, only online tests such as DGA and moisture analysis are done on a periodic basis and other tests are conducted as per the expert's recommendations. DGA analysis shows the distribution of key gases dissolved in oil[1]. These gases are generated due to thermal and electrical faults, and give an indication of the presence and severity of the fault. Further tests such as thermal imaging (infrared image of temperature variation) and acoustic emission-based partial discharge source location are used to detect location of fault. For oil-filled transformers, thermal imaging is used to observe high and low-voltage external bushing connections, cooling tubes, cooling fans and pumps, and the surface of critical transformers [2]. Acoustic monitoring of tap changers detect arcing, contact wear, and timing and mechanical malfunctions.

However, at times, offline tests (Frequency Response Analysis for voltage signal frequency change due to core or winding movement) or invasive tests (Degree of Polymerization for change in polymer chain of insulating paper indicating degradation) are required to confirm the fault [3, 4, 1].

Huge amount of costs are involved in diagnosing and correcting faults. Hence, it is important to have better diagnostic procedures or a combination of techniques to detect probable failure and its root cause. This diagnostic capability will include a

[1] Key gasses formed by degradation of oil and paper insulation are hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO) and oxygen (O_2). Carbon monoxide, carbon dioxide (CO_2) and oxygen are formed because of degradation of cellulose (paper) insulation

list of probable faults so that preparations for necessary corrective action can be planned in advanced and executed quickly. Building a Fault Diagnosis (FD) system to address such issues in power transformers is a complex task. This whitepaper suggests an integrated framework as a potential solution. In addition, some Artificial Intelligence (AI) techniques are suggested for specific tests such as DGA.

Framework for Overall Fault Diagnosis System

The core of this framework is an Expert System shell that drives the diagnosis. It forms the high-level diagnostic layer and includes the flexibility to use tools that form the low-level diagnostic layer as well as capability to examine various contexts under which the diagnosis needs to be carried out. Such an FD system comprising of automated tools built using AI will enhance the users' ability to make decisions efficiently. The system can add intelligence to existing systems to enhance problem solving ability and maintain a broad range of knowledge about a particular domain. It can be used for capturing, organizing and reapplying knowledge including decision rules with specific criteria. An integrated framework will include flexibility to allow different forms of tools to exist and be maintained individually under one common roof.

A low-level AI tool uses a set of rules to categorize numeric data (such as sensor readings), to perform analysis limited to an individual diagnostic test or a part of the equipment. Enhanced tools such as Artificial Neural Networks (ANN) can approximate any unknown input-output relation. These can use specific history data and can also adapt to new data. In contrast a higher level expert system takes into account plant design information and functionality of specific units and diagnostic tests, conditions to trigger the tests and also the weighting criteria for combining results from various test procedures. Diagnostic algorithms can be used for automatic modeling and hierarchical reasoning. The Expert system takes into account symbolic information issues which are poorly handled by tools such as ANN. There can also be multiple layers defined for the low level tool, which can be based on complexity required.

See Figure 1 for a candidate integrated hierarchical FD system for power transformers. Note that the figure includes both – low level AI toolset and high level expert system, and a fusion of various transformer tests based on reasoning and importance. The high level expert system is used when the low level AI model fails to give a clear fault resolution (CFR). It also shows that the expert system seeks additional test information if a clear resolution is not reached. Such a system will develop a life cycle profile of the transformer object.

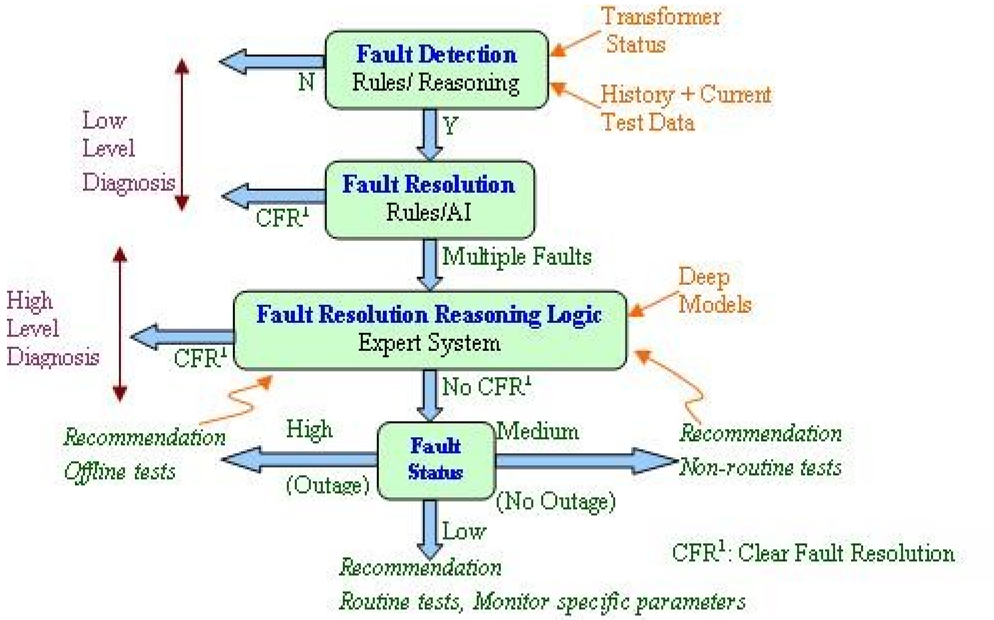

Figure 1: Candidate Structure of Integrated FD System for Power Transformers

The FD system for Power Transformers considers the integration of various phases for diagnosis:

1. Live transformer
   - Frequently monitored data (DGA, temperature, moisture data)
   - Data generated as part of the diagnosis 'on request' (Furan analysis for assessing degradation of cellulose, Thermal imaging, Partial discharge monitoring)
2. Transformer under outage
   - Data generated with the transformer offline but not opened (Recovery Voltage Measurement test to measure winding moisture content, Impulse test for insulation integrity, Frequency response test for detecting winding movement due to loss of clamping pressure or by short circuit forces)
   - Data generated with transformer open (Visual, Degree of Polymerization test)

AI methods can be used for enhancing resolution of fault identification from each of the above tests. This helps to make necessary decisions and take corrective actions by fusion of information from multiple tests and including other available information. Development of such a knowledge base involves different forms of models depending on the depth of knowledge required. Depending on the type of diagnostic procedure and the available knowledge, appropriate tools from the following list can be used for different scenarios:

1. Shallow Models
   - Diagnostic Rules (Empirical models/ Use of standards)

- Data Driven Models: (ANN, FUZZY, SVM)

2. Deep Process Models
    - Thermal process models
    - Transfer function models
    - Equivalent Circuit models
3. Case History Data Base

The following sections explain how the framework described earlier is used to build low-level and high-level layers.

Case Use of Framework

Consider a scenario where ANN is used as technique of choice in the low-level diagnostic layer. A hierarchical ANN diagnostic structure trained on DGA can provide useful fault detection information, even though it cannot determine the location or cause of the actual fault. Output from low level diagnosis can be a list of possible (multiple) faults where CFR has not reached. The expert system (high-level diagnostic layer) then analyses the output and confirms one of the ANN diagnosis as fault or offers an alternative action.

In another sample scenario, two different ANN models (low-level diagnostics) are used–one for DGA to confirm the fault and another for thermal imaging (for fault location determination). Assume that DGA network provides an indication of a 'severe thermal fault'. The expert system (high-level diagnostics) will then combine the two results from both ANN models along with the structural information of the transformer to indicate location of the fault. This can be made flexible to handle even new (unknown) faults. Embedding ANN (or any other form of lower level diagnostic tool) within an expert system is an effective architecture for a fault diagnostic system.

Need for Building Higher Level FD Layer

Failure Mode and Effect Analysis (FMEA) is required to compile information on faults and possible ways to detect them. Additionally, typical problems faced by operators also need to be addressed. Consider the following example, where the transformer is gassing and the cause needs to be determined. The sources of gas generation in a Power Transformer include:

- Dielectric system (Moisture/particles contamination)
- Electromagnetic system (Local core overheating/sparking associated with the main magnetic flux or that associated with stray flux)
- Current carrying circuit (Progressive rise of contact resistance)
- Mechanical system (Loosening of clamping , Winding distortion)

Hence the final step will be to zero-in on any of the above sources correctly.

Using this logic, a DGA analysis is done first classify faults as thermal or electrical. The next step is to determine the involvement of different areas that can produce this fault. Depending on DGA fault type, thermal, electrical faults are assessed. See Figure 2 and Figure 3 for details.

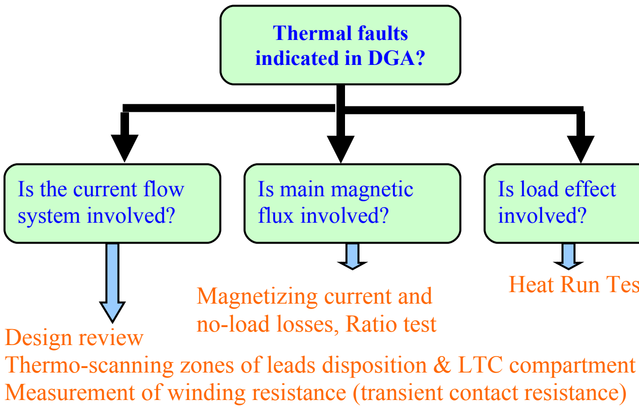

Figure 2: Steps when thermal fault indication in DGA

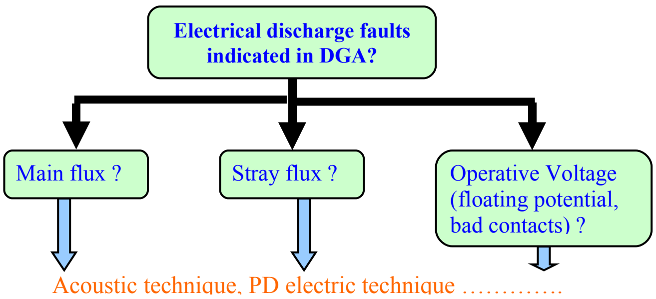

Figure 3: Steps when electrical fault indication in DGA

Using these techniques, a flowchart can be compiled (within Figure 1 architecture) for possible steps to rectify gassing. This logic is used to build the expert system to provide appropriate suggestions for further tests to be conducted or integrate results from different levels of tests for detailed diagnosis.

Low Level AI Techniques

The low-level AI toolset consists of techniques that provide analysis limited to an individual diagnostic test or a part of the equipment [5]. These can be techniques such as ANN, fuzzy and SVM to address a particular test. Use of such adaptable techniques allows for continuous incorporation of new information, and these also take into account aging of the equipment. As an example, use of AI for improving traditional rule base/standards of DGA is discussed here.

The limitations of a traditional DGA analysis are as follows:

- Currently different methods such as IEC/ IEEE/ Duval/ Rogers Ratio based on various standards are followed. .
- Each rule base results in ambiguity when determining the actual fault for certain ranges. There is also approximately 20% chance that results these different methods do not converge to a particular fault type.
- The rules do not result in any probability measure for fault detection, giving rise to ambiguity in case of multiple faults.
- An Expert is required to pin-point the fault (that is, convergence issue to identify the correct fault). The Expert in turn examines additional parameters and test results to arrive at a final conclusion.

The above limitations are solved in multiple steps by AI. First, individual methods are made adaptable by changing the boundaries of fault classes. By doing this, most ambiguity is removed from the results. Also, results from different tests are combined together to arrive at a single output based on probability and significance. Expert knowledge is also added in the form of a rule base.

The proposed solution to improve individual methods includes use of techniques such as Extended NN [6], evolutionary fuzzy logic [7] and support vector machine (SVM) [8]. For example, IEC standard for DGA interpretation uses a range of ratios (3 gas ratios are used) to classify faults. An obvious approach to improve the prediction accuracy is to write fuzzy rules by using fuzzy membership functions to make the boundaries of different classes of faults adaptable to the individual transformer. Instead of using crisp boundaries, fuzzy reasoning scheme invokes adaptable fault class boundaries. Evolutionary fuzzy logic method thus allows for updating membership functions by adapting to new test data. It also has a provision to update the probability of fault identification to be implemented in fault identification [9].

On the other hand, Extended NN uses the concept of extension set to extend fuzzy logic values from limited range of [0 1] to an infinitely wide range. It allows for simpler definition of the NN that has no hidden layer. The output fault classification is directly related to the input nodes, where associated weights are in the range of the 3 gas ratios. This method has been found accurate to detect multiple faults along with associated probability of fault detection.

SVM is based on statistical learning theory and works using feature space of the measured data. Unlike ANN, SVM can learn the non-linear high dimensional space of variables using small number of samples to classify them or to find the multivariate relation between them using regression.

In summary, a hierarchical AI structure for DGA (embedded in low-level diagnostics) can provide useful fault detection information, even though it cannot determine the location or cause of the actual fault. The expert system (high-level diagnostics) activates the AI diagnosis to generate the potential fault list by combining various test results.

Conclusion

Use of AI offers the potential of reducing manpower and financial overhead required by utilities to assess transformer condition. Today, utilities are willing to invest in conditional monitoring equipments such as sensors and connectivity devices. Therefore, manufacturers are under pressure to design fault diagnosis techniques that allow remote monitoring. A need has been felt to structure and maintain these equipments effectively for large plants.

In addition, the ideas presented in this paper can be used by transformer manufacturers to build an FD system for more complex analysis. This can also include the field performance of transformers from its different factory outlets to cater to design and performance improvements of poor performing transformers.

References

[1] *US Bureau of Reclamation FIST Manuals, 3-31, Transformer Diagnostics, June 2003.*

[2]*http://www.maintenanceworld.com/Articles/mt-online/Solving-Electrical-Problems-thermal-Imaging.html*

[3] *Wang, M; Vandermaar, A.J; Srivastava, K.D. "Review of condition assessment of power transformers in service" in Electrical Insulation Magazine, IEEE Vol 18, Issue 6, Nov/Dec 2002 pp. 12 – 25.*

[4] *US Bureau of Reclamation FIST Manuals, 3-30, Transformer Maintenance, October 2000.*

[5] *S.D. Kaminaris, A.X. Moronis, N.I. Kolliopoulos, A.P. Sakarellos, V.T. Kontargyri, S.D. Kampanaros, I.F. Gonos, "PTME – a new expert system application for Power Transformer Troubleshooting and Maintenance", in Proceedings of the 6th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering and Data Bases, Corfu Island, Greece, February 16-19, 2007 pp. 52-57.*

[6] *Meng- Hui, Wang, Hung-Cheng, Chen, Kuei-Hsiang, Chao, Kuo-Hua, Huang "Combined Extension Neural Network and Multi-Regression Analysis Method for Yearly Load Forecasting" IJCSNS International Journal of Computer Science and Network Security, VOL.6 No.12, December 2006 pp.109-114.*

[7] *Yann-Chang Huang Hong-Tzer Ym, Ching-Lien Huang "Developing a New Transformer Fault Diagnosis System through Evolutionary Fuzzy Logic" IEEE Transactions on Power Delivery, Vol. 12, No. 2, April 1997 pp. 761-767.*

[8] *L.V.Ganyun, Cheng Haozhong, Zhai Haibao, Dong Lixin; "Fault diagnosis of power transformer based on multi-layer SVM classifier" Electric Power Systems Research, Vol. 74, 2005, 1-7.*

[9] *Dr. D.V.S.S. Siva Sarma and G.N.S. Kalyani, "Application of AI techniques for non-desctructive evaluation of power transformers using DGA" International Journal of Innovations in Energy Systems and Power, Vol. 2, no. 1, June 2007, pp. 37-43.*

Acknowledgements

The authors thank Dr. Phanibhushan Sistu, Head, EIS R&D for his keen support in this activity.

About Tata Consultancy Services (TCS)

Tata Consultancy Services Limited is an IT services, business solutions and outsourcing organization that delivers real results to global businesses, ensuring a level of certainty no other firm can match. TCS offers a consulting-led, integrated portfolio of IT and IT-enabled services delivered through its unique Global Network Delivery Model, recognized as the benchmark of excellence in software development.

A part of the Tata Group, India's largest industrial conglomerate, TCS has over 143,000 of the world's best trained IT consultants in 42 countries. The company generated consolidated revenues of US $6.0 billion for fiscal year ended 31 March, 2009 and is listed on the National Stock Exchange and Bombay Stock Exchange in India. For more information, visit us at www.tcs.com

Contact Details

jessy.smith@tcs.com, b.vrao@tcs.com