

FAULT DETECTION IDENTIFICATION FOR POWER TRANSFORMERS
PROTECTION

HAIDER KAMIL ABDALSADA

UNIVERSITI TEKNOLOGI MALAYSIA

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HAIDER KAMIL ABDALSADA

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DEDICATION

This thesis is devoted to,

Whoever honored me by bearing his name is my martyr father (Kamel AbdelSada, may God have mercy on him), who sacrificed everything for us to reach the highest ranks and obtain this high educational degree. But, he left before he saw the fruits of his cultivation.

The light of my eyes, the light of my path, the joy of my life. Mom, then mom, then mom. Her prayers and words were a company of brilliance and distinction.

All my dear uncles. In particular, my uncle, Professor Nafea Abdel-Sada. The owner of the great credit after God Almighty and my father in reaching what I am now.

All my dear brothers and sisters.

My dear wife and children helped me greatly in my scientific career.

Everyone taught me a message. Everyone who supported me, even with a smile, and all my dear friends.

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ABSTRACT

The stability of the power system is dependent on the reliability of the various components in the network. A power transformer is a critical component of a power system's transmission and distribution infrastructure. However, it is susceptible to a wide range of problems, which can lead to power outages, which in turn can have a significant economic and social impact. Detecting and analyzing internal faults in a power transformer is a complex process that requires the use of appropriate fault detection procedures to ensure that the related repercussions minimized. Internal and external defects can be found in transformers. In addition to asymmetrical faults and faults from line to ground and line to line, winding flaws and winding insulation failures can cause turn-to-turn or ground faults, depending on the kind of external fault. Magnetic inrush current, lightning strikes, long-term overload, and failure of the cooling system are all possible causes of insulation deterioration. Dissolved gas analysis (DGA) is frequently used to discover transformer faults in the early stages. With the Duval Triangle as a focal point, this thesis provides the basics of introduction to DGA transformer interpretation. Precision in DGA laboratory findings may impact the accuracy of DGA diagnosis, as demonstrated by this study. Both the previous gas levels and the lowest gas levels in service above which diagnostics can be attempted are listed below. There are certain users who are apprehensive about using triangular coordinates even though the Duval Triangle approach is specified in the IEC Standard and through these public assessments. In addition to this effort, MATLAB was used to construct a specialized machine learning approach (MLT) for the detection and classification of transformer faults. Measurements on two separate sets of transformers, one in good working order and the other with various faults, provide the necessary data for MLT training and testing (axial displacement, radial deformation, disc space variation, and short circuit of winding). The suggested method for fault detection is projected to produce comparable results to existing approaches because of its excellent MLT facilities during the learning and testing stages.

ABSTRAK

Kestabilan sistem kuasa bergantung pada kebolehpercayaan pelbagai komponen dalam rangkaian. Pengubah kuasa ialah komponen penting dalam infrastruktur penghantaran dan pengagihan sistem kuasa. Walau bagaimanapun, ia mudah terdedah kepada pelbagai masalah, yang boleh menyebabkan gangguan bekalan elektrik, yang seterusnya boleh memberi kesan ekonomi dan sosial yang ketara. Mengesan dan menganalisis kerosakan dalaman dalam pengubah kuasa adalah proses yang kompleks yang memerlukan penggunaan prosedur pengesanan kerosakan yang sesuai untuk memastikan kesan yang berkaitan diminimumkan. Kecacatan dalaman dan luaran boleh didapati dalam transformer. Sebagai tambahan kepada ralat dan ralat asimetri dari talian ke tanah dan talian ke talian, kecacatan belitan dan kegagalan penebat belitan boleh menyebabkan ralat belokan ke belokan atau tanah, bergantung pada jenis ralat luaran. Arus masuk magnet, sambaran petir, beban berlebihan jangka panjang dan kegagalan sistem penyejukan adalah semua kemungkinan penyebab kemerosotan penebat. Analisis gas terlarut (DGA) sering digunakan untuk menemui kerosakan transformer pada peringkat awal. Dengan Segitiga Duval sebagai titik fokus, tesis ini menyediakan pengenalan asas kepada tafsiran pengubah DGA. Ketepatan dalam penemuan makmal DGA mungkin memberi kesan kepada ketepatan diagnosis DGA, seperti yang ditunjukkan oleh kajian ini Kedua-dua paras gas sebelumnya dan paras gas terendah dalam perkhidmatan di atas yang mana diagnostik boleh dicuba disenaraikan di bawah. Terdapat pengguna tertentu yang bimbang tentang menggunakan koordinat segi tiga walaupun pendekatan Segitiga Duval dinyatakan dalam Piawaian IEC dan melalui penilaian awam ini. Sebagai tambahan kepada usaha ini, MATLAB digunakan untuk membina pendekatan pembelajaran mesin khusus (MLT) untuk pengesanan dan pengelasan kerosakan transformer. Pengukuran pada dua set transformer yang berasingan, satu dalam keadaan berfungsi dengan baik dan satu lagi dengan pelbagai kerosakan, menyediakan data yang diperlukan untuk latihan dan ujian MLT (anjakan paksi, ubah bentuk jejari, variasi ruang cakera dan litar pintas penggulangan). Kaedah pengesanan kerosakan yang dicadangkan diunjurkan menghasilkan keputusan yang setanding dengan pendekatan sedia ada kerana kemudahan MLT yang sangat baik semasa peringkat pembelajaran dan ujian.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
MLT	Machines Learning Technology
ML	Machines learning
LV	Low Voltage
HV	High Voltage
DC	Direct Current
SMPS	switches mode power supplies
RF	Radiofrequency
DGA	Dissolves Gas Analysis
ANFIS	Artificial neural fuzzy inference systems
PHM	Prognostics and Health Management
CS	Cuckoo Search
BP	back propagating
AI	Artificially intelligences
PCA	Principals of the Components Analysis
3D	Three-dimensional
2D	Two-dimensional
FDD	Fault Detection and Diagnosis
ONLOAD TC	on-loads- tap changers
ELM	Extremes Learning Machines
RBF	radial basis function networks
PPM	parts per million
NF	No-Fault
TMDs	Transition metal dichalcogenides
FID	Flame Ionization Detector
TCD	Thermal Conduction Detector
C ₂ H ₄	ethylene
C ₂ H ₂	Hydrocarbons
H ₂	Hydrogen
CH ₄	methane

C ₂ H ₆	ethanol
CO ₂	carbon oxides
O ₂	<i>oxygen</i>
N ₂	<i>Nitrogen</i>
SVM	Support Vector Machine
K-NN	K-nearest neighbors
D1	Discharge of low Energy
D2	Discharge of high Energy
T1	Thermal Fault <300 °C
T2	Thermal fault 300°C-700°C
PD	Partial Discharge
DT	Combination of Electrical and Thermal

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CHAPTER 1

INTRODUCTION

1.1 Problems Backgrounds

The facts in the power's systems, are that the transformers are the ones of the most important significances the pieces of pricey equipment's, in power's electricity systems, it is inevitable that their failure will have a substantial negative influence on the power's supplies that's may result at the catastrophic at blackout as well as highest maintenances that cost. As a result, most critical responsibility in system electrical power is to ensure the dependability of transformers are defects detection technologies that are properly implemented may also significantly cut power transformer maintenance costs, while simultaneously ensuring steady and dependable power supply.

In the power generation and power transmission lines system (power distribution and transmission network), Transformers are the important elements that play the major roles of the formations of the main structures on system power networks.

Transformers are the most important part of the generation and transmission network. It plays a very necessary role that in transferring power electricity from generation site to transmission lines and from there to the distribution stage. Various type in transformer is widely used at power's distribution networks, they have types, including, single-phase, oil-filled, and dry single-phase, and those are a part of the three-phase banks to provide power to consumers. The failure that occurs in single-phase and the three-phases transformer leads to disruption at electrical power supply and often leads to major breakdowns in the processing system, financial losses and the suspension of some factories and public services, and sometimes-human losses. The

failure that often occurs in power transformers and leads to a short circuit between the coils is the deterioration in the insulation property of the transformer windings, and

This is an important and pivotal thing for researchers in this field. The detection in the initial stages of the failure in the overlapping coil of transformer winding is not easy, especially when diagnosing and examining by traditional methods such as conventional differential relay protection mechanisms. In such cases, the error appears as a short circuit in the coil, so the differential relay operation and the phase of the short circuit are very possible and lead to great and serious damage to the coil and the iron core. Researchers all the time struggle in development by keeping pace with scientific development and developing new techniques that fit the need to detect and diagnose faults and study manufacturing faults for overlapping coils. With all these, the practical implementation involves a few challenges, including high reliability, high accuracy, high cost, and the need to add and install new equipment inside the transformer housing, which may lead to an increase in size.

In addition to that, the development in communications system, especially the Internet, may not be sufficient in the speed of transmission and diagnosing faults.

In this thesis, the mechanism of the detections to classifications of the faults in the transformers will be determined using the theory's specific machine learning technique which (MLT) is implemented using MATLAB environment.

1.2 Problems Statement

Transformers are the most important paramount in the systems networks of supply and transmitting electrical energy to consumers, and any fault or defect in it may cost a lot of money. It may take a long time to fix them if small mistakes are not detected early, which may grow and grow and become catastrophic mistakes. Troubleshooting in transformer system is a major concern in power system protection. To preserve the electrical power system and minimize further social and economic

expenses caused because of the interruption of loads, diagnostic measures must be identified the quickly and implemented. The two types of transformer's faults, that might have occurs: are internal flaws and external issues faults (insulations deteriorations, windings failures, overheats, and contaminations of oils). If the insulator fails, the phase-to-phase faults may be classified. As an internal fault as well, which may result in a short circuit and the transformer ceasing to function properly, External-fault is the second kind of fault: (lightning strikes systems overloads, short-circuits).The effect of externals-faults is that occur the outside of transformers that cannot generally to avoided or prevents during conventional the maintenances. Transformer subject to thing such as the lightning strike or other damages from the outsides cannot be prevents. This work designs a catalytic approaches the detection to classification the transformer fault at electric power transmission system. The differential relay is one of the main protections on the transformers acting on internal fault on the transformers such as turns-ground faults and turns-to-turns faults on transformer winding. The internals fault of the transformers can be modeled is modifying the coupling inductance matrix of transformers. If an internal faults at transformer, conductors the inductance matrix will change due to the fault point. This new matrix depends on the location the types of faults. Simulation the defectives transformers will produce the wrong waveform that can be using to tests correctness and sensitivity at differentials protections.

1.3 Aim of the Thesis

The subsequent points can review and summarize the aims of this thesis:

1. Diagnosis the system status, whether in the normal operation or faulted.
2. Detection the fault will be fast and accurate by using the machine learning technique which (MLT) is implemented using MATLAB environment
3. Classify the type of the fault.

1.4 Objectives of the Study

In order to investigation and to classification, the fault which is internal faults protection system at the transformer; it proposed to build the internal faults modeling to be simulating using a real fault waveform system. Followings are the objectives proposed for this thesis: -

1. To analyze and verify the model, the results from the no-load test and the load loss test from the transformer. The test result can also be to use for model analysis and verification.
2. To diagnose the fault after obtaining accurate information and data from the suspects and comparing them with the information available from the database.
3. To evaluating faults to avoid major faults in the systems power sources and ensure that, transformers does not break down significantly.

1.5 Scope of the Study

From the above facts, it can be clearly conclude that the current available techniques for transformer condition monitoring suffer from some limitations.

1. The transformer winding modeling done to define and test the proposed method is a parameter model. This model implemented using SIMULINK MATLAB.
2. Certain tests are necessary to detect the integrity of the windings transformer's away from, its installation in real system.
3. Some algorithms in identifying and detecting faults in transformers require placing sensors or sensitive coils with a sensing property and a high-precision sensitivity fault to detect faults in a short circuit of single turn winding.
4. Using machine learning to develop algorithms that classify faults in electrical power transformers using voltage sag measurements.

1.6 Significance of the studies

The purposes of the thesis are to identifying the classify faults at power transformers, in orders to decreases risks of the transformers failures and detect them before accidents in distribution and electrical transmission stations occur. therefore to identify the differentiate fault from the externals fault, several approaches based on digital's signals process and the artificial intelligence's technologies are used in the Powers transformers need to be protected. The applications of two types of the machines learning algorithm, at vector supports machines and the rondes forests, to distinguish between both (internals, exterior flaws).

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