TRANSFORMER CONDITION ASSESSMENT USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

As a result of the deregulations in the power system networks, utilities have been competing to optimize their operational costs and enhance the reliability of their electrical infrastructure. So, the importance of implementing effective asset management plans that improve the life cycle management of the electrical equipment is highlighted. From an asset management point of view, commonly practiced maintenance strategies are considered to have large portions of redundant costs. Therefore, applying cost-effective, reliable and conditionally-based maintenance policy is a priority. Having certain and comprehensive condition assessment of the electrical equipment supports the selection of the appropriate maintenance plan.

Power transformers are the most costly electrical infrastructures; hence, condition assessment of power transformers is a necessary task. It is a well accepted fact that the remnant useful life of the transformer paper insulation determines its useful operational life. Thus, reliable and economic transformer's insulation condition monitoring and diagnostic techniques are necessary to conduct a comprehensive and efficient transformer condition assessment.

In this dissertation, artificial neural network is utilized as a modeling tool to predict transformer oil parameters. Accordingly, the diagnosis efficiency of several transformer condition monitoring techniques are enhanced and both corrective

maintenance and end-of-life assessment costs are reduced. The research is focused in predicting parameters able to diagnose both transformer insulating oil and its paper insulation condition. Transformer insulation resistance parameter is used as an input for an artificial neural network prediction-based model to estimate transformer oil breakdown voltage, water content and dissolved gases. Moreover, furan content in transformer oil is predicted using artificial neural network with step-wise regression as a feature extraction tool.

An effective prediction model of oil breakdown voltage, water content, dissolved gases and carbon dioxide to carbon monoxide ratio with prediction accuracies of 97%, 85%, 88% and 91% respectively is achieved. The excellent prediction accuracies achieved reduces inspections' time of unplanned outages. Furthermore, Oil quality parameters and dissolved gases are verified to be statistically significant inputs for the correlation with transformer oil furan content. The correlation is confirmed with a prediction accuracy of 90%. By achieving such accuracy, assessing the transformer's solid insulation and ultimately verifying its useful remaining life is approached.

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LIST OF ACRONYMS

AM	-	Asset Management
RCM	-	Reliability-Centered Maintenance
TBM	-	Time-Based Maintenance
CBM	-	Condition-Based Maintenance
CM	-	Condition Monitoring
H_2	-	Hydrogen
CH_4	-	Methane
C_2H_4	-	Ethane
CH_6	-	Ethylene
C_2H_2	-	Acetylene
CO	-	Carbon Monoxide
CO_2	-	Carbon Dioxide
IR	-	Insulation Resistance
DGA	-	Dissolved Gas-in-oil Analysis
BDV	-	Breakdown Voltage
TDCG	-	Total Dissolved Combustible Gases
TCG	-	Total Combustible Gases
ppm	-	Part per million
TS	-	Tensile Strength
DP	-	Degree Of Polymerization
ANN	-	Artificial Neural Network
MLP	-	Multi-Layer Perceptron
RAD	-	Relative Aging Degree
HV	-	High Voltage

LV	-	Low Voltage
TV	-	Tertiary Voltage
SSR	-	Sum of Squares Regression
SST	-	Sum of Squares Total

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CHAPTER 1

INTRODUCTION

1.1 Transformer Asset Management

Transformer life cycle management has been the main concern to asset experts. The main objective behind implementing transformer asset management (AM) plans is reducing the operational costs of the transformer in service and extending its utilization period economically. Condition assessment and maintenance are the main elements of applying transformer AM. Condition assessment requires implementing condition monitoring and diagnostic and end-of-life assessment techniques. Based on the transformer condition, different maintenance strategies are assigned. Applying cost-effective and sufficient transformer condition assessment and maintenance processes leads to obtaining optimum transformer AM.

Several transformer AM strategies have been proposed. An intelligent system is proposed using fuzzy logic modeling to support an optimum and reliable transformer management decisions, like replacement, refurbishment and relocation[22]. The model depends on transformer criticalities, rate of aging, and remnant life as its main inputs. The model has the potential to provide accurate assessment; however, implementing it acquires major costs. The model suggests using large number of advanced CM techniques, which require high conduction and interpretation expenses in terms of money and expertise. Another approach is a condition-based AM strategy utilizing standard diagnosis of CM techniques. The standard diagnosis methods have been utilized to derive a failure probability model in terms of the electrical, mechanical, thermal stresses and life time [2]. This model has not specified a well established set of CM techniques, which reduces the opportunities of practical implementations for this model.

Transformer health index is determined using inspections tests on transformers [3]. The health index method recommended is found to be useful for determining the transformer probability of failure and calculating its remaining life. However, performing health index modeling has difficulties, especially when lack of organized data base of the transformer condition occurs.

It is concluded that implementing reliable and accurate CM techniques, practicing optimized maintenance plans and estimating the transformer remnant life accurately leads to applying developed asset management strategies[4].

1.2 Transformer maintenance plans

Currently, the most common maintenance procedures followed in utilities are corrective maintenance, preventive maintenance and reliability centered maintenance. These three strategies represent the three main generations of maintenance starting from the first generation, which is corrective maintenance and passing by the preventive maintenance strategy until reaching recently reliability-centered maintenance (RCM).

1.2.1 Corrective Maintenance

Corrective maintenance is basically conducted whenever an alarm or trip occurs on the equipment causing an unplanned outage. Recently, corrective-based maintenance strategy on a transformer is considered as a poor approach. This is because corrective action on a transformer can have a cost that is equal to its replacement. For example, refurbishing a tripped transformer requires a lot of testing and inspection time, especially if an internal fault takes place. Therefore, long lasting transformer outage cost is the main concerning consequence of implementing corrective maintenance on a power transformer. However, transformer corrective maintenance can decrease costs for certain faults that are not crucially affecting the transformer operating status. In general, corrective maintenance is a useful approach only if it is accompanying other maintenance strategies.

1.2.2 Preventive Maintenance

Preventive maintenance is considered as the most safe maintenance strategy as incipient faults can be prevented by implementing preventive maintenance. Applying preventive maintenance procedures depends on conducting comprehensive condition monitoring and diagnostics activities on the transformer's parts, like internal insulation, external insulation and control circuits. The time span between conducting these tests is selected based on the type of preventive maintenance technique used by the utility.

Two different types of preventive maintenance are practiced by the utility. The first approach is Time-Based Maintenance (TBM). TBM is implemented when the time span between the transformer testing and inspections is fixed. Time based maintenance has been the most common applied maintenance strategy among utilities before raising the AM thinking. Taking into consideration transformer reliability into service, time based maintenance reduces the failure risks immensely, especially if the time span between the inspections of the transformer is short. However, this approach consumes huge manpower and planned outage costs. Moreover, transformer faults and unplanned outages may occur during the time between the preventive maintenance inspections; particularly when the time span between inspections is long.

The second approach is Condition-Based Maintenance (CBM). CBM is the most acceptable form of preventive maintenance as it cuts down manpower costs. This type of preventive maintenance mainly focuses on applying detailed and comprehensive Condition Monitoring (CM) and diagnostic techniques to the transformer to form clear and accurate assessment about its condition. Such accurate assessment helps the asset manager to develop asset maintenance plans and assign optimized time spans between maintenance activities. Online CM of a transformer is a vital element of implementing CBM to detect incipient faults in early stages. So, in cases of faults detections, CBM reduces the repair costs in terms of spare parts, expertise and time. However, online CM has large conduction cost. Besides, interpreting condition monitoring techniques and scheduling effective time spans between maintenance activities are not easy tasks to be performed.

1.2.3 Reliability-Centred Maintenance

Reliability-centered maintenance (RCM) is found to be the most optimum maintenance strategy that combines the advantages of different maintenance strategies and merges them in a comprehensive and optimized form. RCM can be called risk-based maintenance as maintenance activities are assigned depending on the degree of risk of the transformer in service. The degree of risk depends on two factors: the probability of failure and its severity. The probability of failure of the transformer depends on the transformer operating conditions like the rate of aging, loading and service age. On the other hand, the degree of risk is determined by analyzing the effect of the transformer under study on the reliability of the network. Cost wise, RCM is efficient as it keeps the transformer operating performance equals to the targeted transformer performance level.

In general, transformer maintenance plan is a key stage of implementing transformer life cycle management since it improves transformer operational costs, performance and risks. Table 1 shows contribution of each maintenance strategy in improving transformer operating parameters.

1.3 Transformer Condition Assessment

Transformer condition assessment has become important as a result of shifting the maintenance strategy to be conditionally-based. To serve as a solid backbone for the transformer asset management plans, condition assessment process has to be comprehensive, accurate and cost-effective. The application of these conditions leads to optimum and reliable diagnosis of the transformer condition in service and facilitates the failure prediction process. Transformer condition assessment has two main stages: condition monitoring and diagnostic of certain parameters and end-of-life assessment. It has been accepted that insulation condition assessment of the power transformer is the most efficient approach towards achieving efficient and reliable transformer condition assessment. The reason is that most of the transformer failures occur due to insulation mechanical, electrical and thermal deteriorations.

Table 1: Maintenance techniques effect on cost, performance and risk

Maintenance Strategy	**Costs**	**Performance**	**Risks**
Corrective Maintenance	• Low manpower costs • High outage costs if the failure requires comprehensive inspection • Sometimes, high spare parts costs	• operational performance level <required performance level	• Highest risk: direct and significant damages
Preventive Maintenance	• Highest manpower costs • Low spare parts cots	• operational performance level >required performance level	• Least risks: failures are prevented using routinely checks
Reliability-Centered Maintenance(RCM)	• Optimized manpower costs • Optimized spare parts costs	• optimized performance: operational performance level =required performance level	• Optimized risks: maintenance priority is assigned based on the degree of risk

Several CM and diagnostic techniques have been developed to inspect the transformer condition. Power transformer useful operating life has been defined as the remaining life of the transformer winding paper insulation [1]-[8]. Therefore, the importance of solid insulation condition monitoring and diagnostic methods has increased.

Updated and reliable end-of-life assessment is necessary for maintaining optimum transformer life cycle management. Critical decision like transformer replacement, relocation and refurbishment are based on transformer remnant life estimation.

1.4 Transformer Insulation System

1.4.1 Transformer oil

Transformer oil is produced as a byproduct of the distillation of crude oil. Transformer oil can be paraffinic oil or Naphthenic oil. The paraffinic oil is composed of alkanes, whereas the naphthenic is composed of cycloalkanes. Naphthenic oil is preferred to be used among utilities as it is superior in gas absorbing tendency and low-temperature applications. Transformer oil is mainly installed in oil-filled transformers as a cooling medium; however, it is considered as reliable insulating material inside the transformer. The quality of oil as a cooling medium and an insulating material in transformers is measured using different electrical, chemical and physical tests. The tests that are related to the research work done is mentioned in this thesis.

Transformer oil is degraded as a result of thermal and electrical internal transformer faults. These faults release energy that is capable of decomposing transformer oil into different gases , which are hydrogen(H_2), methane(CH_4), Ethane($C2H_4$), Ethylene(CH_6), acetylene(C_2H_2), carbon monoxide (CO) and carbon dioxide (CO_2). Transformer oil can decompose CO and CO_2 as a result of its oxidation.

1.4.2 Transformer Solid Insulation

Solid insulation material in power transformers is mostly made up of Kraft paper. Kraft paper consists of cellulose, which is a natural linear polymer of cyclic β-D-glucopyranosyl monomers, hemicellulose and lignin. The cellulosic chains are bonded inter-molecularly and intra-molecularly by the hydrogen bonds via the hydroxyl groups in a crystalline and amorphous regions forming at the end fibrils and fibers that support the Kraft paper mechanically. These fibrils and fibers are linked by the amorphous regions of hemicelluloses and lignin. The main failure cause of Kraft paper insulation has been referred to the loss of its mechanical integrity due to the loss of the hydrogen bonds and the deterioration of the fibers.

Oil-impregnated cellulose is degraded due to three main mechanisms, which are hydrolytic degradation, oxidative degradation (pyrolysis mechanism) and thermal degradation.

Hydrolytic degradation is activated by the presence of hydrogen ions separated from acids. Acid-hydrolysis breaks the hydrogen bonds in the cellulosic chains yielding the glucose rings. This mechanism is followed by dehydration reactions yielding furan derivatives. Furfuraldehyde, which is a stable compound to acids, is produced from Xylan, while cellulose yields hydroxylmethylfurfural. The later is not stable to acids, thus laevulinic acid and formic acid are formed. This process of acid catalyzed hydrolysis produces a sum of two water molecules, which cause carboxylic acids to dissociate yielding hydrogen atoms [9].Therefore, Acids and water content can be regarded as accelerators for cellulose paper degradation. Several studies have reported the accelerative effect of water in reducing the cellulosic insulation life[9]-[11].

Pyrolysis degradation consists of the oxidation of the hydroxyl groups to form the carbonyl and the carboxyl groups permitting the chain scission of cellulose.

At temperature less than 200 ℃ cellulose insulation is thermally degraded producing glucose molecules, moisture, carbon oxides and organic acids, while different thermal mechanism applies for temperature more than 200℃.

1.5 Transformer Insulation Assessment Techniques

There are several well understood and common insulation testing and diagnostic techniques practiced as maintenance procedures in power utilities. Insulation monitoring and diagnostic techniques that are related to the conducted research in this thesis work are mentioned in this chapter.

1.5.1 Insulation resistance test (Megger test)

Insulation resistance (IR) test is one of the most classical routine diagnostic tests performed on the power transformer. Usually, it is conducted in routine time-based maintenance along with oil quality tests and dissolved-gas-in-oil-analysis (DGA) to monitor the transformer insulation system and construct an informative and efficient trend analysis. Moreover, IR test plays an important role in the cases of unplanned transformer outages' activities as it contributes to the verification of the occurrence of an internal fault or severe deterioration in the insulation system. IR has certain drawbacks affecting its diagnosis efficiency. The measurement of IR is affected by the contamination and temperature of the insulation system. Temperature has a major influence on the IR measurement, especially in oil filled power transformers. The insulation system in oil filled transformers consists of insulating oil and solid paper insulation where their insulation resistances are affected by temperature independently. So, insulating oil temperature should be noted when conducting megger test. Contamination of the insulating oil can reduce the value of the IR; therefore, oil break down voltage (BDV) and water content tests are conducted along with IR in corrective maintenance process to verify the presence of contamination in the insulation system. Moreover, IR is not efficient in detecting incipient faults that occur due to the operation of the Buchholz relay. The response of the IR as an insulation quality parameter to the presence of incipient faults is slower than the Buchholz relay. Accordingly, DGA is conducted along with IR test to detect incipient faults in emergency unplanned outages. Oil BDV, water content and dissolved gases are considered as important parameters conducted in corrective maintenance activities for inspecting and diagnosing the tripped transformer.

Table 2: IEC 60422 recommended action limits for oil BDV and water content testing [12]

Property	Category	Recommended Action Limit
		Poor
Breakdown Voltage	170-400kV	<50
	72.5 - 170kV	<40
	<72.5kV	<30
Water Content	170-400kV	>10
	72.5 - 170kV	>15
	<72.5kV	>25
Acidity	>72.5kV	>0.15
	<72.5kV	>0.13

1.5.2 Oil quality tests

Breakdown voltage: Oil BDV measurement gives an indication about the presence of contamination resulting from degradation reactions and moisture in the oil. However, BDV has a slower response to contamination particles when compared to other oil quality parameter. This imposes the need to conduct other maintenance checks to the oil like water content and interfacial tension.

Water content: Water content is a reliable parameter as it can measure the transformer insulation system deterioration state. Water content is considered as both an accelerator for the aging process and as an aging product. Water moves from transformer paper insulation to the dissolved form in oil as oil temperature increases and travels back to paper insulation as temperature decreases to achieve water equilibrium in the oil-paper system. Therefore, an accurate diagnosis of the presence of moisture in transformer oil requires a temperature effect correction.

Acidity (Neutralization number): Acids in transformer oil are considered as accelerators of paper insulation aging through hydrolytic degradation. Table 2 shows the recommended action limit for BDV, water content and acidity as per IEC 60422 standard. The standard basically specifies for maintenance engineers the oil quality of transformers with different ratings by referring to the measurement of oil BDV, water content and acidity.

1.5.3 Dissolved gas-in-oil analysis (DGA)

Dissolved gas-in-oil analysis is one of the most acceptable methods used to detect internal incipient faults in the power transformer. Internal faults cause the hydrocarbon oil and cellulose paper in power transformer to emit different gases like, H_2, CH_4, C_2H_4, CH_6, C_2H_2, CO and CO_2. Depending on the concentrations of these gases, the type of fault and its severity is detected. DGA has great diagnosis efficiency as it is used to anticipate transformer incipient faults. According to IEEE C57.104 standard, actions can be taken based on the transformer oil Total Dissolved Combustible Gases (TDCG) as shown in Table 3. The standard recommends the oil sampling intervals and operating procedures along with stating the transformer condition based on the measurement of the TDCG.

CO_2/CO ratio has been accepted as prominent parameter that indicates paper insulation involvement in transformer incipient faults. According to IEC 60599 standards, a value of less than three of the CO_2/CO ratio indicates paper insulation involvement in an internal transformer fault. Merging the two parameters, TDCG and CO_2/CO ratio, CO_2 can be approximated to get the total combustible gases (TCG), which serves as a maintenance planning and diagnosis tool. Table 4 shows the Westinghouse standard for planning maintenance checks based on the concentration of TCG.

However, DGA does not show efficiency in predicting aging and providing general view about the cellulose insulation degradation. Except, CO and CO_2, all dissolved hydrocarbon gases in transformer oil are emitted due to the deterioration of oil only.

Table 3: Actions based on TDCG according to c57.104 [13]

	TDCG Levels (ppm)	TDCG rates (ppm/day)	Sampling Interval	Operation Procedure
Condition 4	>4630	>30	Daily	Consider removal of service
		10—30	Daily	Advise Manufacturer
		<10	Weekly	Exercise extreme caution. Analyze for individual gases. Plan outage. Advise manufacturer
Condition 3	1921-4630	>30	Weekly	Exercise extreme caution. Plan outage
		10--30	Weekly	Analyze for individual gases
		<10	Monthly	Advise Manufacturer
Condition 2	721-1920	>30	Monthly	Exercise extreme caution. Plan outage
		10--30	Monthly	Analyze for individual gases
		<10	Quarterly	Advise manufacturer
Condition 1	≤720	>30	Monthly	Exercise extreme Caution. Analyze for individual gases. Determine load dependence
		10--30	Quarterly	Exercise extreme Caution.
		<10	Annually	Analyze for individual gases. Determine load dependence. Continue a normal operation

Table 4: Westinghouse guidelines on TCG [13]

TOTAL COMBUSTIBLE GASSES	RECOMMENDED ACTION
0-500 ppm	Normal Aging Analyze again in 6-12 months
501-1200 ppm	Decomposition maybe in excess of normal aging Analyze again in 3 months
1201-2500 ppm	More than normal decomposition Analyze in one month
2500 ppm and above	Make weekly analysis to determine gas generation rate contact manufacturer

1.5.4 Tensile Strength (TS)

Tensile strength has shown a sufficient capability to assess the cellulose material degradation. Different life prediction models of power transformers have been proposed using TS confirming that the end-of-life criterion for transformer reliable operation is when its oil-impregnated cellulose paper reaches to 50% of its initial TS value [16]. Another model is proposed in [15] showing that transformer paper insulation can maintain its mechanical integrity until it reaches 20% of its initial TS value using the wide-span and the zero-span measurements (tensile index).

1.5.5 Degree of Polymerization (DP)

Degree of polymerization, which is defined as the average length of the cellulosic chain, measured by the average viscometric method is more convenient method than TS and molecular weight for analyzing the Kraft paper aging [16]. It is found that DP is strongly correlated with TS. The end-of-life criterion for power transformers in service is determined to be around DP of 250 [10]. It is found that TS is constant when DP is in the range of 500-950, then TS decrease directly with DP in the range of 200-500. DP is found to have a tan-sigmoid relationship with temperature. The decrease in DP starts at 70℃, which is the normal operating temperature for power transformer, reaching the maximum rate of change at 100℃ until getting to the end-of-life criteria for transformer solid insulation (DP of 200) at 150℃ [10]. DP has been strongly correlated with paper contaminants and found to be the most useful parameter for assessing the transformer solid insulation [17]. The solid insulation life of the power transformer is predicted, with limited accuracy [16], by modeling the kinetics of cellulose degradation using DP. It is proposed that ($\frac{1}{DP}$) is directly related to aging time [9], [18]. However, a kinetic model derived by finding the average molecular weight has showed that the rate of bond scission ($\frac{1}{DP}$) is not an accurate method [16].

1.5.6 Oil furan content

All the mentioned parameters are credible in terms of assessing the paper insulation degradation; however, they are destructive and costly to conduct. The measurements taken to find the TS, DP and the molecular weight of cellulose insulation paper should be conducted on paper samples taken from the transformers in operation. This way of sampling requires transformers' outages which is costly to the utilities. Therefore, furans' concentration in transformer oil can be a promising indirect measurement to the aging of transformer paper insulation.

Furan content measurement consists of measuring six furfurals dissolved in transformer oil that differs in their stability. Furfurals are composed of 2-furaldehyde (furfural), 5-hydroxymethyl-2-furaldehyde, 2-furoic acid, furfuryl alcohol, 5-methyl-2-furaldehyde and 2-acetyl furan compounds where 2-furaldehyde is the most stable compound for measurement. Furans as degradation measurements of transformer solid insulation have gained wide acceptance in utilities as it is more practical to sample the oil online without the need to have a transformer outage. Furthermore, furan content can be a complementary monitoring technique to DGA. Furans in transformer oil have superiority to detect paper insulation degradation over oil quality measurements and DGA as they are products of the degradation of only paper insulation and have been correlated with other paper aging measurements.

Several researchers have introduced furans as efficient and practical tools for transformer condition assessment and its life cycle estimation. A large scale survey conducted on large population of mineral oil transformers is presented in [18]. It has been found that certain thresholds for the furans' concentrations in transformer oil does exist and can rank the transformer operating state from healthy to poor. The remaining transformer life was calculated using statistical method based on the distribution of the transformer population. The study confirmed that the total furan concentration in transformer oil is more reliable indicator of paper degradation than each individual furan, although each individual furan compound can be useful for indicating types of faults and their severities [19]. A comprehensive diagnostic method is derived based on statistical correlations between transformer internal gases and oil quality parameters and furfural [21]. Trend analysis is used in [21] utilizing the correlation between DGA and furfural to diagnose transformer aging.

In [7], experience is utilized to interpret the furanic compounds concentrations using two developed approaches, which are the percentile score approach and the prediction of degree of polymerization (DP) approach. Further investigation has led to forming a relationship between the concentration of furfural and DP [22]

1.5.7 Artificial Intelligence Applications in Transformer Condition Monitoring and Diagnostic

Attempts have been conducted to predict transformer insulation quality parameters. A successful prediction of BDV and interfacial tension has been performed using a cascade configuration of artificial neural networks with IR resistance as input feature vector for the used model [23]. Polynomial networks have shown their prediction capability in the cases of shortage of number of training samples to correlate BDV and interfacial tension with IR [24]. However, in [23]and [24], the proposed models have failed to predict both transformer oil water content and DGA. Therefore, these proposed models failed to offer comprehensive and cost-effective CM monitoring and diagnostic technique. To be comprehensive and cost-effective, especially in emergency transformer outages, prediction of BDV, water content and dissolved gases should achieved. Therefore, by limiting the model to predict BDV and interfacial tension, costs of conducting the other tests remain and the required time for testing in outages situations is huge and costly. A reliable neural network (NN) and polynomial regression models were presented successfully to correlate BDV with oil acidity, oil water content and transformer age [25]-[26]. Except for few cases, the percentage error between the actual and predicted values of transformer breakdown voltage was less than 10%. However, the model needs the water content and total acidity as inputs to predict the breakdown voltage, which makes the model relatively costly. Megger test is the preferred input for predicting transformer oil quality parameters as it is one of the cheapest and easiest CM tests. Besides, still prediction of transformer dissolved gases for detecting incipient faults is not approached; therefore, proposed models in [25]-[26] are not cost-effective.

Predicting dissolved gases in transformer oil has been attempted recently to facilitate the condition assessment process and reduce its costs. Support vector machine method with genetic algorithm is used to forecast the transformer oil dissolved gases [27]. The model has predicted different dissolved gasses with maximum percentage error of 6.7%. Similarly to what has been presented in [26], the model requires the history data for the dissolved gasses for each unit to be predicted. Such requirement limits the generalization of the model. Trend of dissolved gases is approximated using grey model, which functions efficiently when a shortage of sampling data occurs [28]. The model proposed in [28] consists of two stages: the forecasting of gases trends stage and incipient faults diagnosis stage using common standards. The proposed grey model has achieved a total absolute mean percentage error of 2.5%. However, from an asset management point of view, utilities prefer to measure transformer oil dissolved gases and get more reliable and clear image about the internal condition of the transformer rather than forecasting DGA. Most importantly, the models proposed in [27] -[28] needs DGA as an input which requires relatively big portion of time for conduction and expertise for analysis. This time is considered extremely costly in emergency outages. DGA prediction approach can be more of great value if it is utilized to reduce the unplanned outage time for a tripped transformer. Self organizing polynomial networks, neural networks, expert systems and fuzzy logic have been utilized to assess the condition of the transformer using DGA [29]-[32]. Self-organizing polynomial networks have shown excellent performance of classifying eight different types of transformer faults. The system has achieved a classification accuracy of 98% for a dependable number of data base of 711 samples [29]. It is found that polynomial networks can enhance the diagnostic efficiency of DGA. MLP ANN has proven its efficiency in diagnosing transformer incipient faults using 150 data base of transformer oil dissolved gases [30]. In [30] different input and output patterns are chosen from different diagnostic standards like IEC and Rogers methods. The proposed ANN has achieved a diagnosing efficiency of 87-100% depending on the input and output patterns chosen. The tendency of transformers' incipient faults and the severity of them are quantitatively measured using fuzzy logic technique [31]. In [32], a combination of multi-layer perceptron (MLP) ANN with expert system has been utilized to classify transformer incipient faults depending on the concentrations of the dissolved gases in transformer oil. The expert system used consists of different modules that represent different types of standards diagnosing different types of faults. The proposed system has sown a better diagnostic accuracy (95%) than MLP ANN (93%) and expert system (89%) alone. The condition assessment process is based on classifying the pattern of dissolved gases in transformer oil to detect developed incipient faults. These models enhance the diagnosis efficiency of DGA; however, diagnosis of transformer solid insulation is not developed. In other words, these models can be more practical if they, in addition to fault diagnosis, have a prediction stage for transformer aging. This solid insulation assessment can improve condition assessment as end-of-life assessment is attained. In addition to that, the previous reviewed models require the conduction of DGA. Cost of DGA conduction is acceptable in preventive maintenance; however, much larger outage cost is acquired for DGA in corrective maintenance.

Artificial neural networks have been proposed, using furfurals as prominent inputs to approximate the aging degree of power transformers [33]. Relative aging degree (RAD) of power transformer is calculated using inputs of paper and oil quality parameters. The inputs to the ANN model used in this study are furfural, volume of carbon monoxide (CO), Interfacial tension and acidity. Later study has proposed ANN model with three inputs, which are CO concentration, carbon dioxide concentration (CO2) and furfural [8] to predict the transformer age. The model is verified using transformer samples in service with mean square error of 3.72%. However, using furfural as an input is a costly approach to conduct by utilities.

1.5.8 Summary

It obvious from the review of the state-of-the-art research in transformer condition assessment strategies using artificial intelligence that the two transformer operational parameters, which are costs and performance, are not minimized in the cases of the corrective maintenance and preventive maintenance. In corrective maintenance procedures, some CM parameters are predicted successfully like BDV and interfacial tension, but others like dissolved gases are not. Therefore, the corrective maintenance conduction time and costs are high. In preventive maintenance, accurate aging degree and solid insulation assessment have been achieved; however, with relatively costly procedures. Accordingly, this research work is concentrated on developing reliable transformer condition assessment strategies through artificial intelligence, specifically ANN. The proposed condition assessment strategies in this thesis should enhance the diagnosis efficiency of CM techniques and minimize the transformer operational costs and performance in both preventive maintenance and corrective maintenance activities.

CHAPTER 2

OBJECTIVES AND CONTRIBUTIONS OF THE RESEARCH

2.1 Objectives

The main objective in this research is to enhance the diagnosis efficiency of CM and diagnostic techniques to provide reliable and cost-effective condition assessment process. Well-organized condition assessment leads to implementing efficient transformer maintenance plans and accordingly transformer AM with an optimized operational costs, performance and risks. Two main studies are conducted in this research, which focus on predicting transformer diagnostic parameters.

The first study concentrates on enhancing the diagnostic efficiency of transformer insulation resistance test in corrective maintenance activities by predicting its accompanying tests like BDV, water content, and dissolved gases using ANN. When conducting a corrective maintenance activity, especially after the operation of the Buckhoulz relay, differential relay and the restricted earth fault relay, successful prediction of these tests can reduce their conduction and diagnostic lasting hours. Therefore, the transformer internal inspection time and the unplanned outage costs of conducting a corrective maintenance activity are reduced.

The second study focuses on achieving a cost-effective and reliable method towards assessing transformer solid insulation. This target is attained by predicting furan content in transformer oil using ANN. Classical, easy to conduct and well understood tests' measurements are used as inputs for an ANN-based prediction model to approach a cost-effective transformer solid insulation assessment model. Reliability is maintained by choosing furan content as a measuring parameter for determining the transformer's solid insulation useful life into service. Therefore, an optimized end-of-life assessment strategy can be accomplished.

2.2 Contribution and Significance of the Research

Classical transformer testing methods, such as Insulation resistance and transformer oil testing, have been recognized among utilities as the most practiced methods. These methods are cost-effective and provide acceptable accuracy for efficient condition assessment. Therefore, several standards are developed to formalize the diagnosis of the insulation resistance and oil testing. Predicting insulation testing parameters using classical testing methods can enhance the diagnosis efficiency of the classical methods with optimizing the cost of maintenance tests in preventive maintenance activities. Considering emergency outages of power transformers, condition assessment of the tripped transformer is an elementary task before reconnecting it to the network. Condition assessment of tripped transformer requires certain tests like IR, BDV, oil water content and DGA. Each test has its own conducting time depending on the availability of resources and the complexity of the test. IR testing is relatively cost-effective in terms of conduction time and activity cost. Therefore, predicting the other tests conducted in the case of unplanned outage using insulation resistance test can reduce the outage time and accordingly the outage cost. In comparing this prediction model with the other prediction models proposed in the most recent research, the proposed model is unique in terms of providing comprehensive assessment through prediction of the important needed parameters rather than predicting some of them for taking a reconnection decision in corrective maintenance procedure. Accordingly, costs are reduced in terms of unplanned outage time, manpower costs and testing costs.

Furan content in transformer oil can enhance DGA diagnosis by indicating cellulose paper deterioration. However, it is not cost-effective to conduct furan content for each oil sample taken from the transformer. Therefore, predicting furan content in transformer oil can enhance the implementation of cost-effective preventive maintenance strategy. Moreover, keeping a track of predicted furan content in transformer oil can give a valuable indication about the remnant reliable life of the solid insulation of the power transformer. As it improves transformers' operational costs and performance, the proposed furan content prediction model is a novel model that can be considered superior to the state of the art models for assessing transformer solid insulation. Predicting furan content as per the proposed methodology utilizes relatively cheap testing inputs to the model which improves the operational performance and costs of preventive maintenance.

2.3 Related Publications

1. Refat Atef Ghunem, Ayman H. El Hag, Khaled Assaleh, and Fatima Al Dhaheri, "Prediction of Furan Content in Transformer Oil Using ANN," Paper is accepted to be orally presented in International Symposium in Electrical Insulation, ISEI, June 6-9, 2010.

2. Refat Atef Ghunem, Ayman H. El Hag, and Khaled Assaleh, "Estimating Transformer Oil Parameters Using Artificial Neural Networks," International Conference on Electric Power and Energy Conversion Systems, EPECS, November 10-12,2009.

More publications are under preparation to be submitted to IEEE Transactions and IEEE Magazines.

CHAPTER 3

MATERIALS AND METHODS

3.1 Transformer Insulation Tests

The transformers under study belong to Abu Dhabi Transmission and Despatch Company. The transformers' service ages vary between 7-15 years. For the first problem under study, which is enhancing the diagnosis efficiency of insulation resistance parameter using ANN, nineteen power transformers are used. The transformers have ratings between 50-140MVA and voltage rating of 220/33/11KV. For the second research study, which is prediction of furan content of transformer oil using ANN, forty transformers are used. The training and testing data used in the model are collected from the transformers' maintenance records for transformers with voltage ratings of 220/33 KV, 132/11 KV, 380/15 KV and 33/11 KV. The oil used in the tested transformers is mineral naphthenic oil.

3.1.1 Megger Test

The IR test is conducted by injecting a 2KV DC voltage into the transformer insulation and the insulation resistances between high voltage (HV) terminal and grounded main tank, low voltage (LV) terminal and grounded tank and tertiary voltage (TV) terminal and grounded tank are determined. The measurement is taken after 15 and 60 seconds until the reading is stabilized; otherwise, the reading is taken after 300 seconds. Figure 1 shows the equivalent schematic diagram of the megger test for HV/ ground measurement. The practical megger test conducted in the site is shown in figure 2.

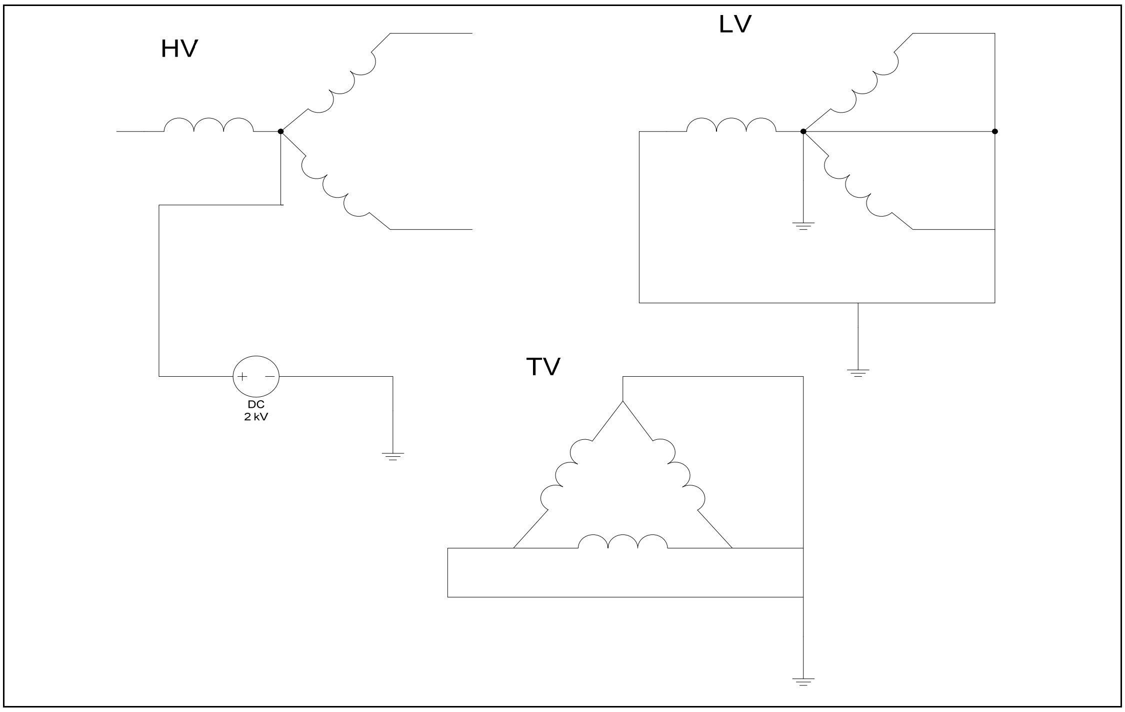

Figure 1: Schematic diagram of Megger test (HV/Ground)

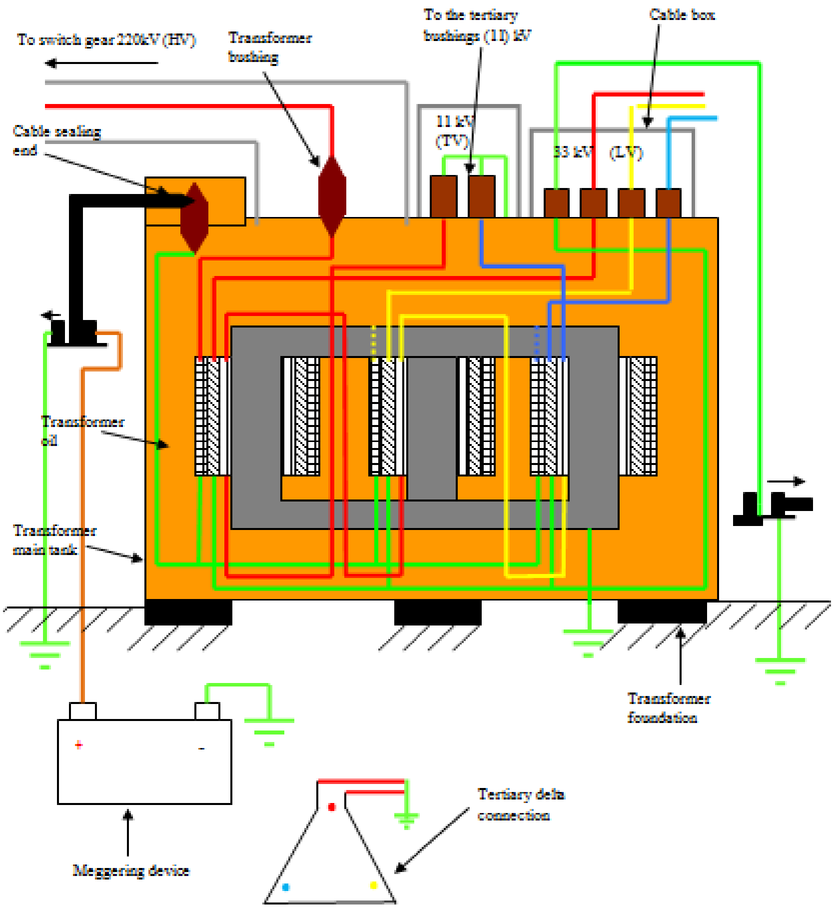

Figure 2: Side view of practical megger test conducted in the site

3.1.2 Oil Quality Tests

The breakdown voltage of the transformer oil sample is measured by applying a gradually increasing voltage between two uniform electrodes with a 2.5mm separation gap as per IEC60156. IEC 60814 standard is used to measure the water content in the transformer oil samples used in the study. The oil samples are taken at a temperature range of 60-65 ºC to reduce the effect of water equilibrium in the oil/paper insulation system. Acidity is measured in chemical lab according to ASTM D974 standard.

3.1.3 Dissolved-Gas-in-Oil Analysis (DGA)

Dissolved gas analysis (DGA) is conducted in the chemical lab using the chromatographic method according to the IEC 60599 standard to find the concentration of the following gases: Hydrogen (H2), Methane (CH_4), Ethane (C_2H_4), Ethylene (C_2H_6), Acetylene (C_2H_2), Carbon Oxide (CO), and carbon dioxide (CO_2). The total dissolved combustible gases (TDCG) are calculated by adding the concentration of the measured gases except the concentration of CO_2. Samples of IR, oil testing and DGA results used in the first study are depicted in Table 5.

Table 5: Sample of the data used in the first study of predicting BDV, water content, TDCG and CO_2/CO ratio using insulation resistance measurements as input features

Insulation Resistance (MΩ)			Parameters			
HV/E	MV/E	TV/E	BDV (kV)	Water Content (ppm)	TDCG (ppm)	CO2/CO
300	240	400	71.4	26.8	497	8.25
820	880	1100	75	30.57	737	7.98
280	280	380	74	16.46	672	6.46
560	580	620	67	22.62	665	6.23
270	220	390	75	17.63	894	4.85
210	160	260	74.2	13.75	1126	4.17

3.1.4 Oil Furan Content

Furan content in transformer oil is measured using high performance liquid chromatography technique according to ASTM D 1533 standard. Table 3 shows samples of the oil testing data used in the second study. It is evident from the table that the transformers oil results cover a wide range of transformer oil conditions.

Table 6: Samples of the oil data used the second study of predicting furan content in transformer oil

TR #	CO (ppm)	CO2 (ppm)	TCG (ppm)	TDCG (ppm)	Water content (ppm)	Acidity (KOH/g)	BDV (KV)	Furan content (ppm)
T1	393	4559	764	5323	39	0.54	28	17.96
T3	193	9128	322	9350	35	0.14	23	14.11
T9	298	2710	342	3052	21	0.19	54	4.23
T15	347	1816	361	2177	7	0.1	57	3.06
T16	229	1230	266	1496	13	0.11	60	2.81
T26	374	2836	577	3413	12	0.03	89	1.57
T36	58	1775	129	1904	14	0.04	58	0.04
T37	122	2386	190	3026	10	0.04	78	0.38
T40	66	1147	78	1225	9	0.02	77	0.19

3.2 Artificial Neural Networks (ANN)

Artificial neural networks (ANN) have been developed to be analogous with the neural system in the human body with simple units called neurons. The neurons are collecting signals from other neurons after being weighted in connection links. ANN has proven their efficiency in different power system applications [34].

3.2.1 ANN Structure Proposed

A multi-layer perceptron (MLP) neural network is used to model the relationships proposed in both studies. The use of ANN as a modeling technique has been proposed due to the non linear and complex relationship between the inputs and the outputs proposed. The problem of predicting insulation diagnostic parameters can be defined physically, which makes it no linear and complex. No linear mapping has been found for such prediction problems before. MLP ANN has proved its efficiency in mapping between nonlinear and complex input and outputs variables. In addition to that, MLP

ANN has been successfully used in transformer insulation diagnosis and condition assessment problems with high accuracy and reliability. Therefore, MLP ANN topology has been chosen as a modeling technique in this research work. The first studied ANN focuses on the relation between IR and oil BDV, water content and dissolved gases. In this study the physical relationship between the insulation resistance as an input and BDV, water content, TDCG and CO_2/CO as outputs is defined physically with an indirect approach. The indirect approach has come from the fact that each parameter indicates different degradation mechanism or is able to diagnose different insulation types. The variation in the diagnosis capability of the parameters makes it more complex. The second studied ANN concentrates on the relation between oil quality parameters and dissolved gases as inputs and furan content in transformer oil as output. Similar to the first correlation problem, the relationship between the oil quality parameters and furan content is defined physically and in indirect way. The fact that DGA is an incipient fault diagnosis technique, oil quality parameters are mainly oil degradation indicators and furan content is a paper insulation assessment technique makes the correlation more complex to be derived. It is a fact that a MLP ANN with one hidden layer can be efficient for any defined correlation problem; however, more than one hidden layer can be efficient in some highly complex and nonlinear problems. As the physical relationships proposed are not defined directly, MLP ANN with two hidden layers for the nonlinear mapping can be more efficient and useful. The need for using two hidden layers can be inferred by examining [23]. The researchers have used a cascade of more than one MLP ANN with one hidden layer to compensate for the indirect physical relations ships between insulation resistance as an input and BDV, acidity and interfacial tension as outputs. In this research, the two defined prediction problems have been experimentally tested using MLP ANN with one hidden layer and different combinations of numbers of the neurons. The achieved model has given low prediction accuracies for most of the testing samples. Therefore, MLP ANN with two hidden layers has chosen to be the modeling technique. Figures 2 and 3 show the MLP ANN architecture used for the two prediction problems.

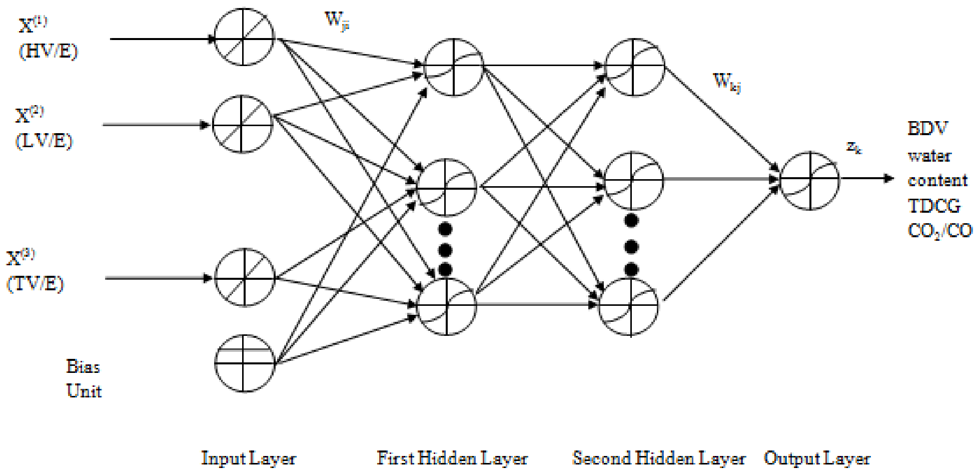

Figure 3 : Artificial neural network structure proposed for predicting BDV, water content, TDCG and CO_2/CO

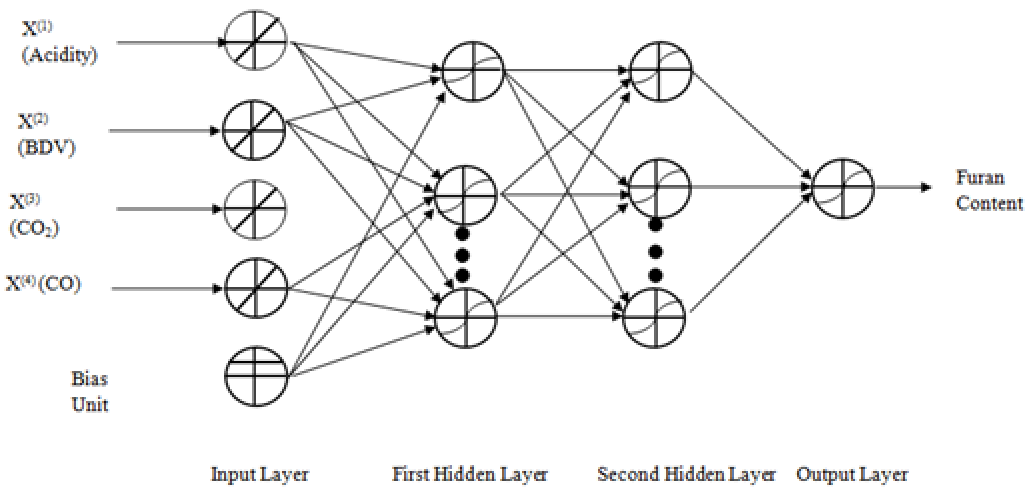

Figure 4 Artificial neural network structure used for prediction of furan content

where $X^{(d)}$ is the dth feature, w_{ji} represents the weights between the i^{th} input unit and the j^{th} hidden unit and w_{kj} is the weights between the k^{th} output unit and the j^{th} hidden unit. The input samples in the first layer are sent to the hidden layer through weighted connection links. The hidden layer calculates its net activation as in the following equation:

$$net_j = \sum_{i=1}^{d} x_i w_{ji} + w_{j0} \quad (1)$$

Where d is the number of features, which is three features in this study (HV/E, LV/E and TV/E) , and w_{ji} represents the weights between the i^{th} input unit and the j^{th} hidden unit. The output of the hidden layer, which is a nonlinear function of its net activation, is shown as the following:

$$y_j = f(net_j) \quad (2)$$

Where y_j is the output of the hidden layer. The output layer calculates its net activation as in the following equation:

$$net_k = \sum_{i=1}^{N_h} y_j w_{kj} + w_{k0} \quad (3)$$

Where N_h is the number of hidden neurons and w_{kj} is the weights between the k^{th} input unit and the j^{th} hidden unit. The output layer yields an output as a nonlinear function of its net activation as shown in the following equation:

$$z_k = f(net_k) \quad (4)$$

where z_k is the output at the k^{th} output unit, which is equal to one in the studied model.

The neural network used in the first model has three neurons in the input layer, two hidden layers with three neurons at the first hidden layer and 10 neurons at the second hidden layer and one neuron at the output layer. The number of the neurons in the hidden layers has been chosen by tuning it until descent prediction accuracy is achieved. Each of the three inputs, which are HV/E, LV/E and TV/E measured insulation resistances, are presented to one of the input neurons. BDV, water content, TDCG and CO_2/CO ratio appear at the output neuron separately depending on the needed predicted parameter. While the second model of prediction furan content in transformer oil has input layer with different number of neurons depending on the number of current inputs used, two hidden layers and one output layer for predicting furan content as an outcome of the ANN. By tuning the number of neurons in the hidden layers until reaching the highest prediction accuracy, five neurons at the first hidden layer and ten neurons at the second hidden layer are found to form the most optimum furan content prediction model.

Tan sigmoid activation function due to its non linearity to map the non linear correlation between the proposed inputs and outputs. Since gradient descent is used, tan sigmoid function is continuous as defined in equation 5.

$$f(net_{j,k}) = \frac{2}{1 + e^{-2 \cdot net_{j,k}}} - 1 \tag{5}$$

The output of neural network can be expressed as a function of the inputs, the weights between input layer and the hidden layer and the weights between the hidden layer and the output layer as per the following equation:

$$g_k(x) = z_k = f\left(\sum_{i=1}^{N_h} w_{kj}\, f\left(\sum_{i=1}^{d} x_i w_{ji} + w_{j0}\right) + w_{k0}\right) \tag{6}$$

3.2.2 Feature extraction using stepwise regression

Stepwise regression is a common feature extraction method that selects the model inputs depending on their statistical significance. Stepwise regression can be of great value when availability of redundant input features of the prediction model occurs, which can cause a reduction in prediction efficiency. Applying stepwise regression analysis requires conducting certain steps that contain measuring the statistical significance of the model approached using the partial F-statistic parameter. Partial F-statistic is determined as shown in the following equation [35].

$$F_j = \frac{SS_R(\beta_j/\beta_0\,, \beta_1, \dots\,,\ \beta_{j-1},\ \beta_{j+1}, \dots, \beta_k)}{MS_E} \tag{7}$$

where β_j is the regression coefficient due to the current added term x_j, $\beta_0, \beta_1, \dots$, $\beta_{j-1},\ \beta_{j+1}, \dots, \beta_k$ are the regression coefficients for the terms currently in the model MS_E indicates the mean square error for the model and $SS_R(\beta_j/\beta_0\,, \beta_1, \dots\,,\ \beta_{j-1}$, $\beta_{j+1}, \dots, \beta_k)$ indicates the regression sum of squares due to β_j given that $\beta_0, \beta_1, \dots$, $\beta_{j-1},\ \beta_{j+1}, \dots, \beta_k$ are already in the model.

For this research work, stepwise regression is an important step for predicting furan content in transformer oil. Stepwise regression can be efficient in testing the possible input features of the model and accordingly an optimum feature modeling step is achieved. Stepwise regression is not utilized in the first research study, which is enhancing the diagnosis efficiency of IR. In a corrective maintenance situation, megger test is conducted first for insulation inspection as it is easier and other accompanying tests are conducted later. Therefore, practically, megger test results are the only and the most optimum input features for the proposed model.

Matlab is used as a feature modeling environment for predicting furan content in transformer oil. Terms are added or removed to the input feature vector depending on the p-value of entering and removing input terms. The p-value represents the null-hypothesis test probability with a tolerance of α for adding a term and a tolerance of β for removing a tolerance. The process starts with an initial model with the first term added. Usually, the first selected input term is the one that has the least p-value provided that it is less than the entrance tolerance. After that, terms are added or removed after calculating the p-value for each step [36]. For a term that is not in the model, the calculated p-value represents the null hypothesis that the term added does not contribute to the statistical significance of the model (has zero coefficient). Similarly, for a term that is already in the model, the calculated p-value represents the null hypothesis that the term does not contribute to the model (has zero coefficient). Figure 5 clarifies the stepwise regression process. It should be mentioned that the entrance and removal tolerances (α & β) are chosen before initiating the stepwise process to be 0.1. Besides, it should be noted that different models with different input features can be achieved depending on the first term added to the model. This variation in the feature vectors reduces the generalization capability of the model and makes it more localized for the sample of data used. Therefore, all combinations of featuring models are analyzed by changing the first selected term each time until using all the features nominated initially.

The statistical parameters used to compare between the analyzed models are Adjusted R^2-statisitc and F-statistic. R^2-statisitc measures the proportion of variation of the predicted variable (furan content in transformer oil) with respect to the selected features in a multiple regression model. R^2-statisitc that is equal to 1 represents the best possible fit in a multiple regression model, while zero R^2statisitc represents worst fit between the input features and the predicted variable. R^2-statistic can be calculated as the following:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{8}$$

where SSR is the sum of squares regression and is calculated as in the following equation:

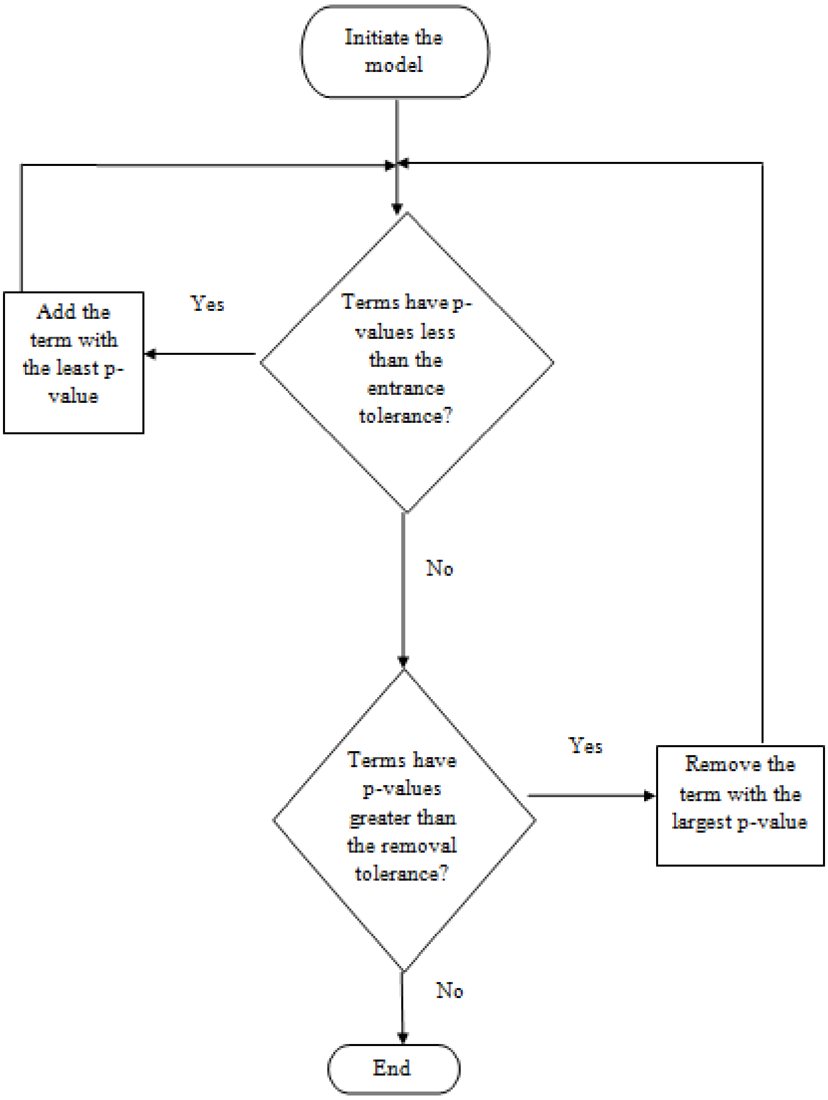

Figure 5: Stepwise regression flow chart.

$$SSR = \sum_{n=1}^{N} (\widehat{Y_t} - \overline{Y})^2 \tag{9}$$

SST is the sum of squares total. SST is calculated as the following formula:

$$SST = \sum_{n=1}^{N} (Y_t - \overline{Y})^2 \tag{10}$$

SSE is the sum of squares error. SSE is calculated as shown below:

$$SSE = \sum_{n=1}^{N} (Y_t - \widehat{Y_t})^2 \tag{11}$$

where Y_t is the actual predicted furan content, $\overline{\mathrm{Y}}$ is the mean of observations of furan content used in the multiple regression model , $\widehat{Y_t}$ is the predicted furan content using the fitted model and N is the number of observations , which are transformer oil samples in this study . However, R-square as a statistical parameter depends on the number of the prediction variables used in the fitted model. This makes the comparison between different models with different number of input variables unfair. Therefore, Adjusted R^2 parameter is used to compensate for the number of input terms when comparing different multiple regression models with different predictors. Adjusted-R^2 is calculated as shown in the following equation:

$$\overline{R^2} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \qquad (12)$$

where $\overline{R^2}$ is the adjusted R^2-statistic, n is the number of observations (transformer oil samples) and p is the number of input variables in the multiple regression model. F-statistic is a measure of the significance of the selected terms to predict the dependent variable, which is furan content in transformer oil in this study. F-statistic is calculated as in the following formula:

$$F = \frac{SSR/p}{SSE/(n - p - 1)} \qquad (13)$$

where SSR is the SST is the sum of squares regression, SSE is the sum of squares error, p is number of variables and n is the number of observations (oil samples).

3.2.3 ANN Training and Testing

Before the training starts, the data is normalized by maximum value normalization criterion to improve the accuracy of the model. The main objective behind using the back-propagation training method is to use training samples of inputs and outputs in the network to adjust the weights' values (w_{ji},w_{kj}) to minimize the difference between the predicted and the actual outputs. The optimum weights (w_{ji},w_{kj}) are learned by minimizing the training error given in the following equation:

$$J(w_{ji}, w_{kj}) = \frac{1}{2}\sum_{k=1}^{m}(t_k - z_k)^2 \qquad (14)$$

Where $J(w_{ji}, w_{kj})$ is the mean square error and t_k is the target output at the k^{th} output unit. Using gradient descent, the updated weights are calculated as the following:

$$w_{ji}^{t+1} = w_{ji}^{t} - \eta \frac{\partial J}{\partial w_{ji}} \quad (15)$$

$$w_{kj}^{t+1} = w_{kj}^{t} - \eta \frac{\partial J}{\partial w_{kj}} \quad (16)$$

Using the chain rule, $\frac{\partial J}{\partial w_{ji}}$ and $\frac{\partial J}{\partial w_{kj}}$ are calculated yielding the following expressions:

$$\frac{\partial J}{\partial w_{kj}} = -(t_k - z_k) f'(net_k) y_j \quad (17)$$

$$\frac{\partial J}{\partial w_{ji}} = -f'(net_j) x_i \sum_{k=1}^{m} (t_k - z_k) f'(net_k) w_{kj} \quad (18)$$

In light of the limitation in the number of samples and to increase the statistical significance of the results, round robin strategy is used in training and testing the neural network. On a leave-k-out basis and cycling over all the samples, k samples of the measured megger and oil analysis data are spared for testing while the rest of the samples are used for training the neural network. Obviously as k increases the number of test combinations increases while the size of the training samples decreases. For the first study of enhancing the diagnosis efficiency of IR in obtaining our predication results we started with k =1 and incremented its value by 1 up to 40% of the number of measured samples. On the other hand, k is maintained to be one for the second study of predicting furan content in transformer oil as statistical significance is attained using stepwise regression.

Table 7 shows the mean square errors and their respective number of epochs of sample of the training of ANNs proposed towards predicting BDV, water content, TDCG, CO_2/CO and furan content respectively. The criteria chosen for stopping the training of the ANNs are reaching zero mean square error or its global minimum until it converges to a constant values.

Table 7: Mean square error and their respective number of epochs for samples of the ANNs proposed to predict BDV, water content, TDCG, CO2/CO and furan content

Proposed prediction output	Mean square error	Number of epochs
BDV	0.001	30
water content	0.01	13
TDCG	0.2	13
CO_2/CO	0.006	30
Furan content	1×10^{-11}	500

It is found that there is a decent mapping between the proposed inputs and outputs is reached. The good mapping is verified using testing inputs for predicting BDV, water content, TDCG, TCG and furan content and then calculating the percentage prediction accuracy using the absolute percentage error (APE) and mean absolute percentage errors (MAPE) criteria. The prediction accuracy of the ANN studied are determined using APE and MAPE criteria as shown in the following equations:

$$APE = \frac{\left|y_{ac}^{i} - y_{pr}^{i}\right|}{y_{ac}^{n}} \times 100 \tag{19}$$

$$MAPE = \frac{\sum_{i=1}^{N}\left(\frac{\left|y_{ac}^{i} - y_{pr}^{i}\right|}{y_{ac}^{n}}\right)}{N} \times 100 \tag{20}$$

Where y_{ac}^{i} is the ith actual output and y_{pr}^{i} is the ith predicted output of the network and N is the number of transformer samples.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Oil Quality Parameters and DGA Prediction Model

4.1.1 Oil BDV Prediction

The correlation between the measured values of the BDV with their predicted values is shown in Figure 6. The average prediction accuracy of the BDV prediction model using leave-1 out strategy is calculated to be 97%. No significant drop in the accuracy of the predicted BDV was noticed when the number of tested samples increased, Table 8. The average accuracy for BDV has only dropped 3% as depicted in Table 8. The proposed BDV prediction model proves the strong correlation between transformer IR and BDV. It is found that the obtained correlation in this study is superior to the results obtained by the models proposed in [23] and [24]. The correlation between IR and BDV comes from the fact that both transformer IR and oil breakdown voltage give an indication about the dielectric capability of transformer oil to withstand high electrical stresses. Although there is the narrow range of variations of BDVs (63.6-78.8 kV) of transformers' oil samples used in the training and testing stages, the generalization capability of the proposed ANN applies. Having an oil sample with a small BDV values (<50) can be considered as a rare case, especially in power transformers. Therefore, the variation band in BDVs used in the study is practically reliable.

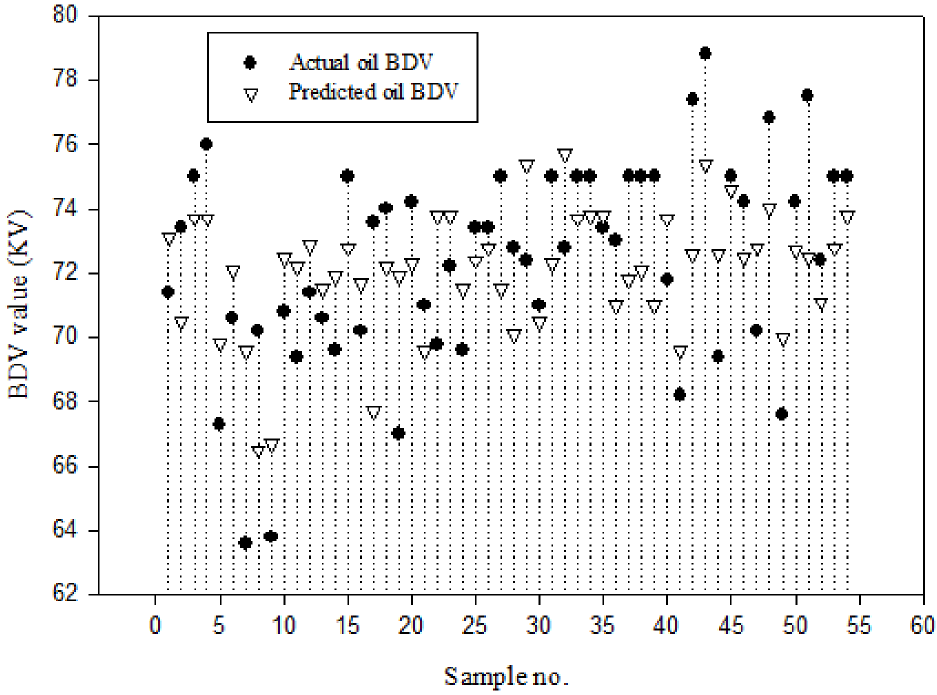

Figure 6: Correlation between insulation resistance and oil BDV.

Table 8: Prediction accuracies of BDV for different sizes of training sets

Size of testing set (samples)	Prediction Accuracy
1	97
2	93
3	93
4	94
5	93
6	93
7	94
8	94
9	94
10	94
11	92
12	95
13	95
14	94
15	94
16	95
17	95
18	95
19	95
20	95
21	92
Average Prediction Accuracy	94

4.1.2 Oil water content prediction

For a training process with leave-1 out strategy, the average prediction accuracy of water content is found to be 85% as shown in Figure 7. Water content in transformer insulation system is recognized as one of the most deteriorating contaminates in transformer oil. This gives an indication about the correlation between oil water content and transformer insulation resistance as they both measure the contaminated degree of the transformer insulation system.

Table 9 shows the prediction accuracies as a function of the size of the tested sample and the average prediction accuracy has been found to be 80%. Similarly to the BDV prediction, the reduction in the model efficiency due to the increase in the testing sample set is not significant (less than 6%). However, compared to BDV the prediction accuracy has been reduced between 10-15%. This can be attributed to the relatively wider scatter of the data of water content (17-32 ppm) compared to BDV (63.6-78.8 kV) and the relatively small size of the training set (31 vs. 54). Moreover, the oil temperature effect in altering the value of the measured oil water content was not completely considered as the oil sample was taken between 60-65 ºC. Such narrow band of temperature variation may still influence the accuracy of the water content measurement. The proposed model to predict oil water content in this study can be considered superior to other proposed models [23] and [24]where the effect of temperature variation on the measured samples was completely ignored.

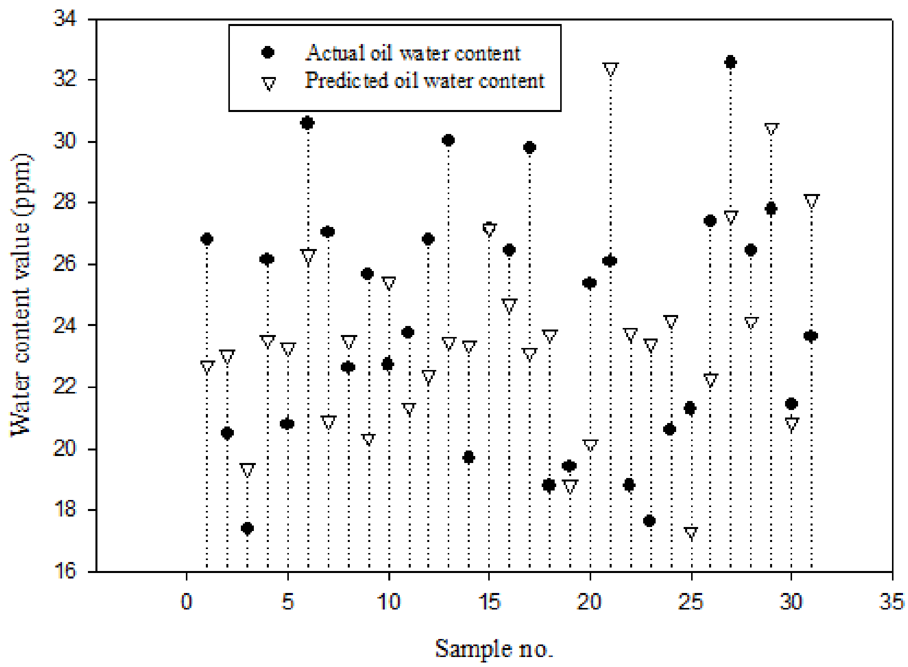

Figure 7: Correlation between insulation resistance and oil water content.

Table 9: Prediction accuracies of oil water content for different sizes of training sets

Size of testing set (samples)	Prediction Accuracy
1	85
2	81
3	81
4	80
5	79
6	80
7	79
8	74
9	81
10	75
11	77
12	83
Average Prediction Accuracy	80

4.1.3 DGA prediction

a. Total Dissolved Combustible Gases (TDCG)

The correlation between TDCG and IR is verified in Figure 8 with a prediction accuracy of 88%. Referring to Table 10, the average prediction accuracy for the overall prediction process after increasing the testing sets' sizes each time by one sample is reduced to 74%. This average prediction rate shows that the correlation between IR and TDCG does exist. Larger size of the training set can improve the performance of the model immensely. TDCG has been accepted as a well informative parameter to indicate the presence of incipient faults and degradation of the transformer insulation system. The degradation process occurs due to the thermal, electrical and mechanical stresses of the insulation materials. The degradation process is accelerated by certain factors like, water content and acids. Internal faults can accelerate the overheating of insulating materials causing the transformer oil and cellulose paper insulation to degrade severely. Insulation resistance is affected by the deterioration and the abnormal excess of degradation, thus, IR can be an indicative parameter to the TDCG. Although TDCG is a reflection of incipient faults rather than a parameter for aging index, an acceptable and reliable correlation between TDCG and IR is verified in the proposed model.

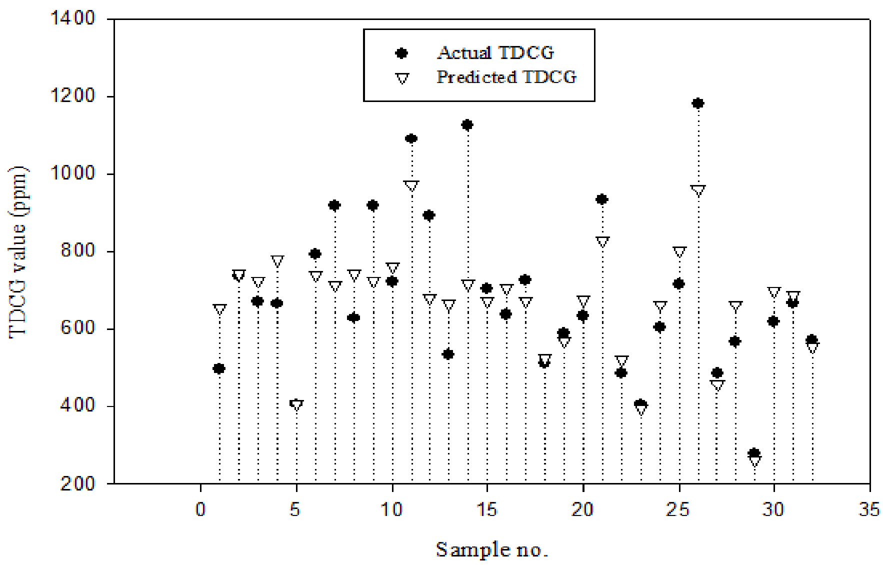

Figure 8: Correlation between insulation resistance and oil TDCG.

Table 10: Prediction accuracies of oil TDCG for different sizes of training sets

Size of testing set (samples)	Prediction Accuracy
1	88
2	74
3	75
4	74
5	69
6	69
7	76
8	76
9	74
10	71
11	74
12	70
13	74
Average Prediction Accuracy	74

b. CO_2/CO ratio

The correlation between CO_2/CO ratio and transformer insulation resistance is depicted in Figure 9. The prediction accuracy for the model in this case is calculated to be 91%. However, Table 11 shows a relatively large reduction of the model efficiency when the number of testing samples increases. The average prediction accuracy after repeating the prediction process for all numbers of testing samples is reduced to 78%. The reduction is attributed to the relatively small number of measured samples used in training and testing the proposed model. CO_2/CO ratio is a good indicator of the cellulosic insulation involvement in internal fault or deterioration of the transformer insulation. A CO_2/CO ratio larger than seven can be due to normal deterioration state of the transformer solid insulation. Both deterioration process and incipient faults have their influence in decreasing the insulation resistance. Although CO_2/CO ratio is more efficient in diagnosing cellulose involvement in incipient faults rather than indicating the deterioration of cellulose, the proposed model shows an acceptable reliability of predicting CO_2/CO ratio. This agrees with the practice in utilities to use CO_2/CO ratio with other insulation quality parameters as indicators for cellulose thermal degradation.

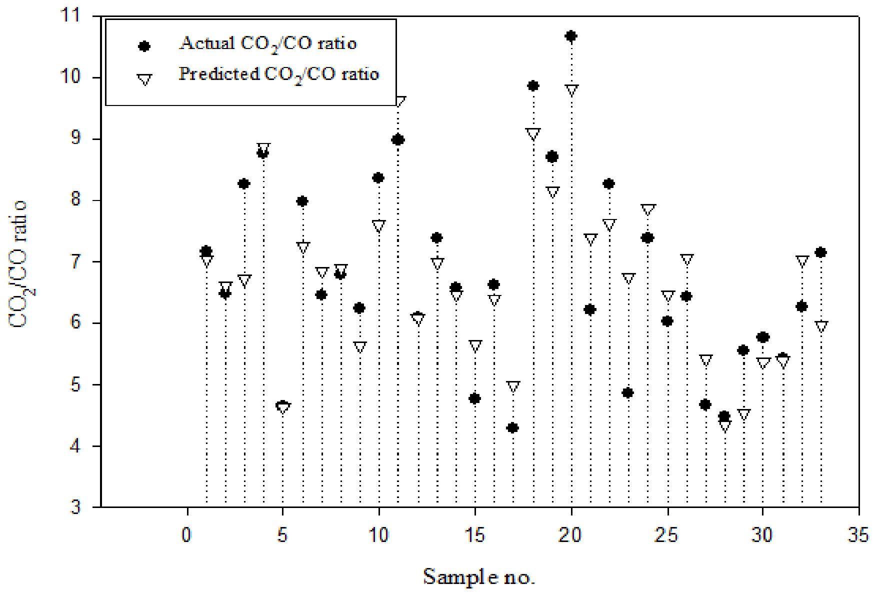

Figure 9: Correlation between insulation resistance and oil CO_2/CO ratio

Table 11: Prediction accuracies of oil CO_2/CO ratio for different sizes of training sets

Size of testing set (samples)	Prediction Accuracy
1	91
2	82
3	76
4	74
5	77
6	84
7	76
8	67
9	80
10	82
11	80
12	75
13	74
Average Prediction Accuracy	78

4.2 Furan Content Prediction Model

Furan content in transformer oil is predicted using ANN by correlating furan content with oil parameters contributing to paper insulation degradation. Different cases are studied in this chapter depending on the input feature vector of the ANN. Stepwise regression is used as a feature modeling method for improving the prediction performance of the model.

4.2.1 Model Input Features

Seven different stepwise regression models with seven different initial terms are statistically tested and analyzed. Matlab is utilized to compute the p-values of the terms that are added or removed. Eventually, the optimum inputs are chosen as shown in Table 12.

Table 12: Selected terms of different tested stepwise regression models

initial term	selected terms
CO	1. CO_2 2. Acidity 3.BDV
CO_2	1. CO_2 2. Acidity 3.BDV
TCG	1. CO_2 2. Acidity 3.BDV
TDCG	1. CO 2. TDCG 3. Acidity 4. BDV
water content	1. CO_2 2. Acidity 3.BDV
Acidity	1. CO_2 2. Acidity 3.BDV
BDV	1. CO_2 2. Acidity 3.BDV

According to the analyzed stepwise regression models, two different models are recommended as shown in Table 12. The first model, which has CO, TDCG, BDV and acidity as input terms, is recommended one time when the initial term is selected to be TDCG. The second model, which has CO_2, acidity and BDV as input features, is suggested six times with CO_2, acidity and BDV as initial features.

Analyzing the rate of occurrences of each of the two models recommended by stepwise regression process, it is verified that the input features in second model are the most statistically significant input terms for predicting furan content in transformer oil. This is obvious when evaluating F-statistic to be the larger for the second model as shown in Table 13.

Table 13: Recommended models by stepwise regression

Model inputs /Statistical Parameter	R-square	Adjusted R-square	F-statistic
CO, TDCG , BDV and Acidity	0.88	0.87	70.69
CO_2, Acidity and BDV	0.88	0.87	98.77

Both of these stepwise regression models show that acidity is a crucial input feature for predicting furan content in transformer oil. The correlation between furan content and acidity comes from the fact that acidity is the main cause of hydrolytic degradation of transformer paper insulation. Hydrolytic degradation yields at the end furan derivatives in transformer oil. Stepwise regression model suggests that CO_2 in transformer oil can be an efficient indicator for transformer paper insulation degradation. This is justified as CO_2 is one of the main resultants of thermal and hydrolytic degradation of transformer paper insulation. CO_2 is found more efficient in assessing the paper insulation in transformer oil than CO in this study. This result verifies what has been found in [16] where it is concluded that CO has weak correlation with paper aging. Moreover, in [19], [20] and [37] CO_2 is found to be more statistically significant for assessing paper insulation deterioration than CO. In this study, CO as an input term is found to contribute to prediction of furan content in transformer oil only when TDCG is used as an initial term in the model as shown in Figure 4. CO_2 is found to be correlated with furan content more than CO that is mainly a resultant of thermal degradation. On the other hand, CO_2 is a resultant of both thermal and hydrolytic degradation, which is the main dominant aging mechanism for transformer paper insulation under normal operating temperatures [11].

BDV is found a statistically significant term for furan content prediction in transformer oil. It is selected as in input feature in the model with highest statistical significance along with CO_2 and acidity. BDV is an efficient indicator of paper insulation in transformer oil; BDV is reduced due to the presence of contamination and particles resulted from the thermal, oxidative and hydrolytic reaction of transformer paper insulation. The correlation between BDV and transformer paper insulation aging is verified in [19].

When compared to CO2, BDV and acidity, the correlation between water content and furan content in transformer oil is weak. At transformer operating temperatures, water content in transformer oil is mainly produced due to the aging of transformer oil as confirmed in [21]. Besides, water content in transformer oil is mainly produced as a result of thermal degradation of paper insulation at temperatures higher than 100 ℃ [16] and [38], whereas furan content measurements under study reflects aging of the transformer at normal operating temperatures.

TCG are not found to be correlated with furan content in transformer oil. This finding is confirmed in [19], where it is stated that TCG is not an efficient parameter for assessing paper insulation degradation. Hydrocarbon gases like H_2, CH_4, C_2H_4, C_2H_6 and C_2H_2 are composing both TDCG and TCG. Hydrocarbon gases are indicators oil degradation; therefore, being part of TCG and TDCG may reduce the statistical significance of TCG and TDCG to predict furan content in transformer oil. So, the addition of CO to the second model is to improve the TDCG ability to contribute to the prediction model. This is because hydrocarbon gases (H_2, CH_4, C_2H_4, C_2H_6 and C_2H_2) that compose TDCG are adding redundancy to CO_2, which is the largest, portion composing TDCG. Therefore, it can be observed that CO can contribute to predicting furan content in transformer oil, but with low significance. In general it can be concluded from analyzing different stepwise regression models that CO, CO_2, BDV and acidity are efficient estimators of furan content in transformer oil.

4.2.2 Oil furan content prediction

The first model proposed in Table 13 is tested using ANN; the proposed input model has a prediction accuracy of 74%. Figure 10 shows the predicted furan contents for the 40 tested transformers along with their actual values. Generally, it can be said that the model has an acceptable accuracy. It can be observed the prediction error is higher in transformers with high concentrations of furan content (10-17 ppm) as shown in Figure 10.

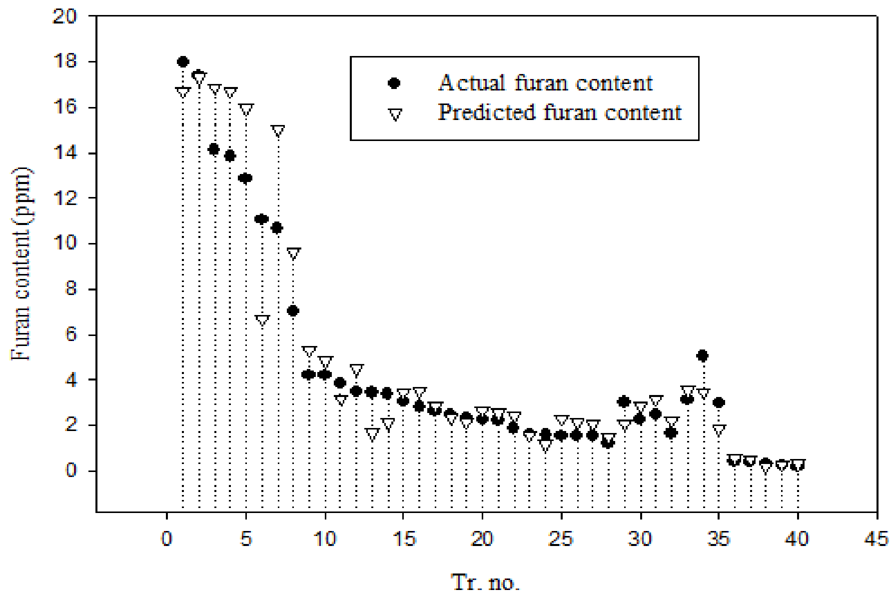

Figure 10: Furan content prediction in transformer oil with CO, TDCG, acidity and BDV as inputs

The second proposed model in Table 13 with CO_2, acidity and BDV as input features is tested using ANN as shown in Figure 11. The prediction accuracy is found to be 85%. It is evident that this model has reduced the prediction accuracy, especially for transformer with high concentrations of furan content (10-17 ppm). The results found for the two models proposed in Table 13 using ANN verifies the results obtained using stepwise regression.

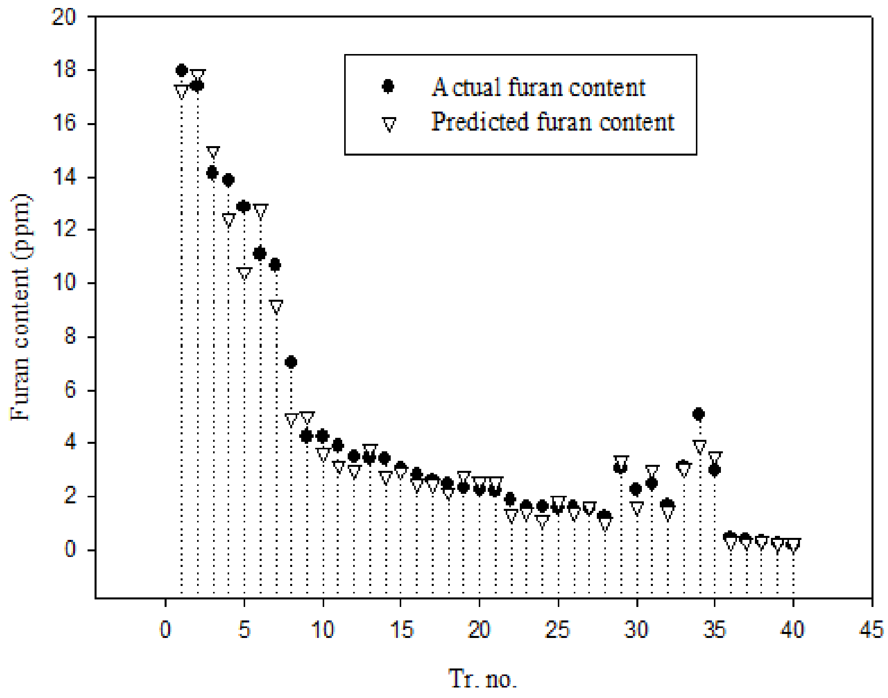

Figure 11: Furan content prediction in transformer oil with CO2, acidity and BDV as inputs

CO is added to the input feature vector along with CO_2, acidity and BDV to analyze the effect of adding CO to the model. Figure 12 shows the actual furan content in transformer oil for the 40 tested transformers along with their predicted values; the prediction accuracy is found to be 90%. This models suggests that CO can improve the performance of prediction model; however, with relatively small significance.

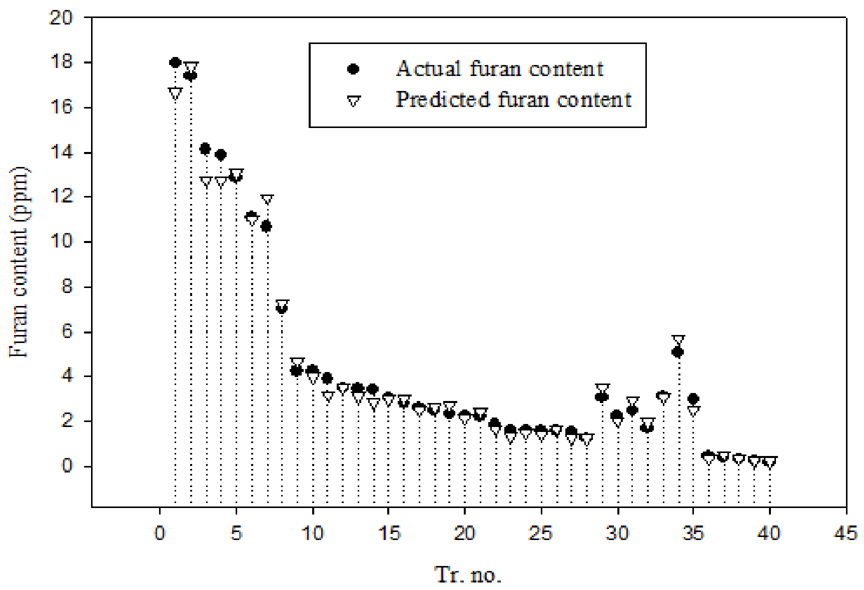

Figure 12: Furan content prediction in transformer oil with CO, CO2, acidity and BDV as inputs

The fourth studied ANN prediction model contains CO, BDV and acidity as input terms, while the fifth model has TCG, BDV and acidity as input features. The redundancy effect of hydrocarbon gases are confirmed as the first model has prediction accuracy of 73%, whereas the prediction accuracy of the second model is 69% as depicted in Figures 13 and 14. Moreover, by comparing the prediction accuracies of the second model (input terms are CO_2, acidity and BDV) and the fourth model (input terms are CO, TDCG, acidity and BDV) it can be assured that CO_2 is more statistically significant that CO for predicting furan content in transformer oil

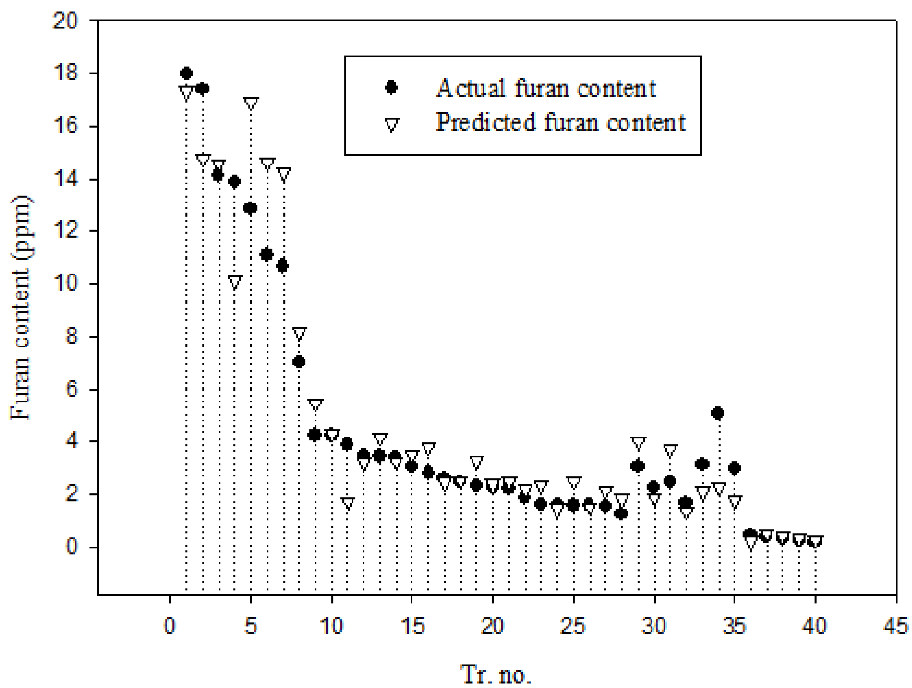

Figure 13: Furan content prediction in transformer oil with CO, acidity and BDV as inputs

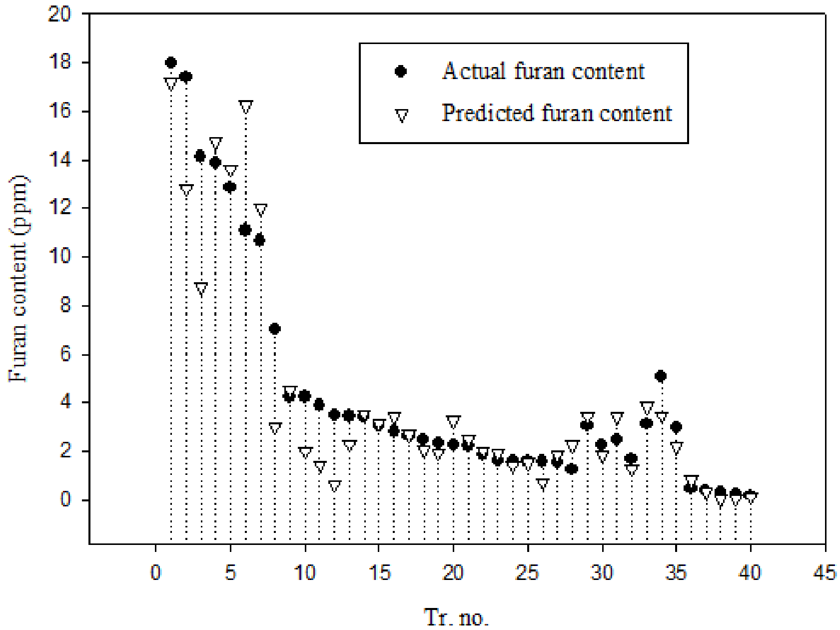

Figure 14: Furan content prediction in transformer oil with TCG, acidity and BDV as inputs

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Prediction of oil quality parameters and dissolved gases

In this thesis, an improvement to different condition monitoring and diagnostic techniques conducted as maintenance procedures is achieved using ANN. ANN has proved its efficiency to predict different transformer insulation diagnostic parameters that are measured during maintenance. Oil BDV, water content, TDCG and CO2/CO ratio are predicted with 97%, 85%, 88% and 91% accuracies respectively using ANN as a prediction tool and transformer insulation resistance as input feature.

The proposed model of predicting BDV, water content, TDCG and CO2/CO ratio to improve IR parameter shows the potential of AI techniques to improve transformer insulation diagnosis and reduce the corrective maintenance costs. Prediction of abnormal internal condition of transformers can be strengthened using the proposed prediction strategy; however, larger size of data is required to have more reliable model. The proposed model can be considered as a cost effective solution to the disadvantage of implementing corrective maintenance on electrical equipment in the system. Predicting transformer quality parameters reduces diagnosis time for the transformer, thus, corrective action can be taken in an immediate manner. Generalization of the model can be a critical issue; however, the proposed models in this study suggests a decent potential for predicting oil BDV, water content, TDCG and CO2/CO ratio. Relatively speaking, efficient and successful prediction is verified for oil BDV and water content. Accepted prediction accuracy and decent generalization capability for the TDCG prediction model has been proposed. However, an improvement is suggested to oil CO2/CO ratio prediction model by increasing the size of measured oil samples used in the training and testing process of the ANN. In conclusion, the proposed correlation method can serve as an efficient tool towards developing instructive transformer life management.

5.2 Prediction of Furan Content

Reliable remnant life estimation of transformer into service has been estimated successfully using a cascade of two processes. The first process represents the feature extraction method for selecting the significant inputs for the prediction model, which is the stepwise regression. The second process composes of predicting the concentration of transformer furan content using ANN. Accordingly, The correlation between furan content and different transformer oil quality parameters has been verified using the partial F-statistic parameter in a stepwise regression feature extraction modeling process. Finally, a successful prediction of furan content in transformer oil is achieved using ANN.

Stepwise regression is found to be a useful tool for extracting the optimum input terms for predicting furan content in transformer oil. The reliability of stepwise regression as an input modeling tool has been realized by verifying its outcomes with conducted experiments mentioned in the literature. However, data with small size can affect the efficiency of stepwise regression to be localized to the available measurements. In addition to that, it should be noted that stepwise regression outcome can differ with different selected initial terms. Therefore, to form a reliable conclusion based on stepwise regression process, all possibilities of initial terms should be included and the largest possible size of data should be used. In this study, ANN is used after stepwise regression to enhancing the generalization of the proposed model to predict furan content in transformer oil and to verify the results obtained from the stepwise regression procedures.

The prediction accuracy of the first studied model with CO, TDCG, BDV and acidity as inputs is 74%, while the prediction accuracy of the second studied model with CO_2, BDV and acidity as inputs is 85%. Therefore, the results obtained from stepwise regression are verified using ANN. CO_2 is proved to be more correlated with transformer paper insulation aging than CO by comparing two ANN prediction models. The first one has CO, acidity and BDV as inputs (prediction accuracy of 73%), while the second one has CO_2, acidity and BDV as inputs (prediction accuracy of 85%). The most efficient model is attained with a prediction accuracy of 90% when CO, CO_2, BDV and acidity as input features to the prediction model. It can be stated that CO has small significance on predicting furan content as the prediction accuracy of has increased by 5% only when adding CO to CO_2, acidity and BDV inputs. Total dissolved combustible gases are found to reduce the prediction accuracy to the prediction model if added to the input feature vector. TCG contains hydrocarbon gases that reflect incipient internal faults in transformer rather than transformer aging. Predicting furan content using routine tests like BDV, water content, acidity and DGA enhance the diagnostic efficiency of these tests. The proposed prediction model improves these tests to be able to diagnose both oil and cellulose deterioration efficiently and mange the transformer life cycle accordingly. Besides, the routine tests used as input features of the model are easier to conduct and diagnose than furan testing.

5.3 Recommendations for future work

The prediction models proposed can be tested on transformers belong to other utilities in other countries with different operating conditions. This testing can verify the generalization and validity of the proposed models. Predicting other insulation quality parameters like interfacial tension and DP can improve the efficiency of the proposed models for assessing the transformer condition. Applying different artificial intelligence techniques like polynomial networks and comparing prediction accuracies can be useful for achieving the most efficient technique.

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