A Group Method of Data Handling for Oil-Immersed Transformer Life Cycle Assessment

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Abstract—*A transformer is one of the most important parts of a power supply system. If a transformer malfunctions during the power generation and supply, the economy and stability of electrical power will suffer significantly. Thus, transformers must be viewed as a critical asset management issue in the generation of electrical power. The management of engineering assets such as transformers, requires real-time diagnosis and preventive maintenance in order to avoid unexpected and catastrophic equipment shut-downs. In addition, the health status and remaining life of the transformer are critical knowledge for proper maintenance and management. This research focuses on oil-immersed transformers as a case study to help managers compile real-time monitoring and sampling data for information systems. These data serve as the basis for diagnostic and maintenance decisions and are used to forecast the transformer's remaining life. The deterioration of the transformation's insulating paper was measured to derive the transformer's remaining life and to project the optimal replacement time. The proposed prediction method uses the Group Method of Data Handling (GMDH) to estimate the remaining life of any given transformer in use. This algorithm uses the dissolved gas-in-oil and furfural formation as the input variables to form the transformer life assessment model. Finally, the derived model is compared to the other models proposed by International Electrotechnical Commission (IEC). The results show improved performance over the currently used IEC's models.*

Keywords—*Engineering asset management, Maintenance recommendations, Failure diagnosis, Life assessment, Oil-immersed transformer*

I. INTRODUCTION

Electric power generation is a n ecessary requirement of daily life. That directly affects the quality of the national economy and people's lives. For example, during the 10th of November, 2009, a massive power outage swept across Rio de Janeiro and Sao Paulo, Brazil. An estimated five trillion people were affected and traffic was paralyzed in the two cities. Experts concluded that the failure was caused by a network power grid failure [1]. The transformer is responsible for converting power voltage and delivering electricity to users in a stable and continuous manner. Ensuring transformers are working in a reliable and economically viable is a critical factor for power industry business operations.

In this paper, we present a case study about an intelligent maintenance platform that uses real-time monitoring information collected from oil-immersed transformers. The functions provided by the platform include detecting the health of the transformer using Doernenburg, Rogers and Duval Triangle diagnostics and estimating the remaining life of the transformer using the Group Method of Data Handling (GMDH) based approach. This approach uses online data to establish the structure of the model and calculates the life loss ratio of the transformer. The proposed method improves the life assessment method provided by the Institute of Electrical and Electronics Engineers (IEEE) and the International Electrotechnical Commission (IEC). Finally, asset managers can quickly study a transformer's status by accessing real-time data and regular reports to formulate maintenance decisions and replacement investment strategies.

II. LITERATURE REVIEW

This section reviews the literature related to engineering asset management, transformer deterioration diagnosis, and the transformer remaining life assessment methods.

A. Engineering Asset Management

Engineering Asset Management (EAM) is an emerging cross-disciplinary field which integrates financial planning, engineering, and information management to assist managers to minimize costs and reduce risky operations failure [2]. According to the definition in Publicly Available Specification (PAS) 55-1 [3], EAM defines "systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan."

One of the tasks of EAM is to minimize the life cycle costs of assets. To achieve this goal, Arshad et al. [4] proposed a condition based maintenance (CBM) tool for transformer management. This tool allows a transformer to operate according to its practicable efficiency. On the other hand, Iung [5] indicated that transformer maintenance should be optimized using remote access technology and multi-agent systems to monitor the real-time state of assets in different locations. The negotiation between the agents is conducted using game theory. The proposed system provides an effective approach to multi-information transmission over inter-organizational teams and reduces response time to schedule maintenance work.

B. The Deterioration Mode of Oil-immersed Transformer Insulation and Effect

Over time a transformer will deteriorate because of the deterioration of oil and insulation. The transformer insulation oil deteriorates because its chemical composition changes when subjected to electricity over time. When the oil deteriorates, impurities in the insulating oil increase which pollutes the oil. Accelerated aging of transformer oil decreases, its dielectric properties and insulating properties.

Inside an oil-immersed power transformer, there are various insulation materials such as insulating paper, Bakelite, laminated board, epoxy, and fiberglass. When something fails inside the transformer, the fault area generates a large amount of heat or causes a high voltage and high temperature discharge. The high temperature further decomposes the surrounding insulation materials into combustible gases, which can dissolve into insulating oil. As a result, the insulating oil interfacial tension decreases and its dielectric strength can drop dramatically [6].

C. Diagnosis Methods for Transformers

Diagnosis analysis, using high-tech condition monitoring equipment and expert knowledge can improve transformer maintenance better satisfy the goals of an organization. Online condition monitoring technology and network services are increasingly used by asset managers. Since temperature is the most critical factor affecting a transformer's life, this paper studies heat-related fault diagnostic methods including the general dissolved gas method, the *Doernenburg method, the Rogers method and the Duval method*.

Dissolved Gas-in-oil Analysis (DGA) is currently the most commonly used diagnostic method. Different faulty locations will generate different types and different quantities of gases which will be dissolved in the insulation oil. Therefore, the gas content in the oil provides evidence for diagnosis. DGA is used for real-time monitoring of transformers. At present, the content and type of gas-in-oil are analyzed based on IEEE and IEC standards. By studying the transformer design details, operating conditions, and gas production rates, then the possible causes of the malfunction and maintenance recommendations can be derived. There are even more specific dissolved methods that have been developed as the designs of transformer have changed over time.

The Doernenburg method analyses the quantities of hydrogen (H2), methane (CH4), acetylene (C2H2), ethylene (C2H4), and ethane (C2H6) in the oil and uses the ratios of four gases to the oil for diagnosis. This method determines three failure types including thermal decomposition, low-intensity partial discharge and high-intensity partial discharge [7, 8]. The Rogers method analyses the same five gases and computes three ratios of four gases for diagnosis. The diagnostic results indicate normal operations, low-energy density arcing, arcing with high-energy discharge and low temperature, temperatures < 700℃, and temperature > 7 00 ℃. The Rogers and Doernenburg methods are similar, but it is simpler to use the three ratios of gas concentrations to make a diagnostic decision [7].

Finally, Duval Triangle method was first described in appendix B of the IEC 60599 [9] document. This method only uses three types of gases (CH4, C2H4, and C2H2) for diagosis. It can be used to detect partial discharge, low-energy partial discharge, high-energy partial discharge, temperature < 300℃ thermal fault, 300 ℃ < temperature < 700℃ thermal fault, and temperature > 700℃ thermal fault.

Furfural compounds are the deterioration product of the fibrous insulation material. A significant increase in furfural concentration indicates that the insulation material has degraded. Therefore, monitoring the furfural concentration in insulation oil can assists in early detection of insulation material degradation more accurately than dissolved gas-in-oil methods [10].

Finally, temperature recorders can also be used for detecting the failures of transformers. The temperature information can be used in combination with oil gas analysis.

D. Remaining Life Assessment Methods

A transformer generally has 20 to 40 years service life. During this period, the transformer requires regular maintenance. Current industry practice estimates the life of oil-immersed transformers based on the status of insulation paper. The reason is that potential failure from the oxidation and degradation of insulating oil, gaskets, or the on load tap-changers can be prevented by regularly replacing the components. However, replacement of aging coil insulating paper is so expensive that normally the complete transformer is replaced.

The commonly used life prediction methods include the method proposed by the Institute of Electrical and Electronics Engineers, the method proposed by the International Electrotechnical Commission. Both methods assess transformer residual life based on extreme winding temperatures but use different parameter settings and computational methodologies. The remaining life of a transformer may also be based on the degree of polymerization and tensile strength of insulation paper. Pradhan and Ramu [11] performed an aging test for insulating paper to monitor changes of carbon monoxide, carbon dioxide, 2-Furaldehyde, total Furan contents, 2-Acetylefuran and 5-Methyle-2-Furfural. Ariffin and Ghosh [12] developed a mathematical method to evaluate the aging of insulating paper on a 33/11 kilovolts (kV) electrical transformer using the measurements of carbon monoxide, carbon dioxide and 2-Furaldehyde to assess the degree of polymerization with a 91% confidence level.

Considering that initial polymer level of insulating paper is not the same due to different insulating properties, Stebbins et al. [13] proposed the following equations for prediction the degree of polymerization and the remaining life of insulating paper:

$$DP = \frac{\left[\log_{10}\left(2 - FAL \times 0.88\right) - 4.51\right]}{-0.0035},$$

$$\%Life\ Used = \frac{\left[\log_{10}(DP) - 2.903\right]}{-0.006021}.$$

E. Other Lifetime Assessment Methods

Researchers have tried other approaches to predict a transformer's deterioration or life, including the Weibull distribution [14], hidden Markov chains [15], Monte Carlo simulation [16, 17] and hybrid algorithms [18]. The Group Method of Data Handling (GMDH) was proposed by Ivakhnenko A.G. in 1968 [19] and can be used for developing mathematical models for complex problems. The method provides an effective way to model complex systems for forecasting and decision analysis. GMDH is well-established and applied in economic forecasting, weather forecasting, and social modeling. For example, Leite da Silva et al. proposed a composite reliability evaluation method based on Monte Carlo simulation and GMDH to assess the reliability of composite electricity generation and transmission. The method effectively reduces data analysis, and rapidly assesses the overall state of a system. Therefore, this method is a good choice for real-time monitoring of power supply systems [20].

III. METHODOLOGY

The application of the Intelligence Maintenance Recommendation Platform for transformers includes four stages. For the first stage, monitoring devices are installed on a transformer to record its changing conditions and plotted on a chart. For the second stage, the malfunctions of the transformer and their causes are diagnosed using the Doernenburg diagnostic method, the Rogers diagnostic method, and the Duval Triangle diagnostic method to analyze the dissolved gas-in-oil. Maintenance strategies are then recommended based on the diagnosis results. For the third stage, GMDH is used to estimate the remaining life of the transformer based on the data from the analysis of dissolved gas-in-oil and the historical sample of furfural compounds. Finally, for the fourth stage, a weekly, a monthly, and annual maintenance plan are derived based on the remaining life prediction. The GMDH based remaining life assessment method is discussed in the following sections.

A. Hypothesis

Filtering and replacement of insulating oil will help minimize deterioration inside transformers. Even though the oil samples are collected before filtering or replacement and the life reduction is predicted, the results can still be inaccurate. Therefore, the GMDH remaining life prediction is based upon the assumption that the insulating oil has not been filtered or replaced. In addition, because of the lack of historical transformer life records, 2-furfuraldehyde (2-FAL), a kind of chemical material, is used to evaluate the degree of polymerization of insulating paper and its life deduction [13].

B. Group Method of Data Handling

The group method of data handling (GMDH) is a set of inductive algorithms that use polynomial models and a hierarchical self-organization process based on external criterion as shown in figure 1.

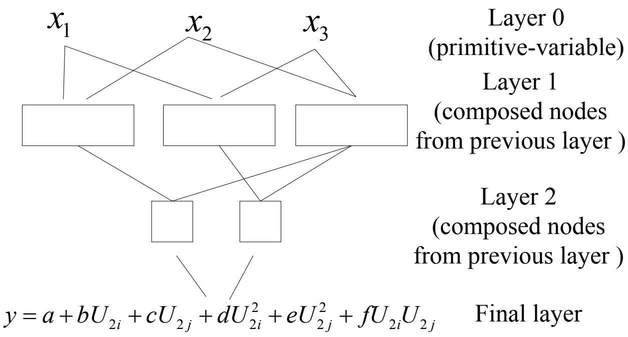

Figure 1: The hierarchical multilevel concept of GMDH

The main steps of GMDH are as follows [21, 22]:

1) Split observational (historical) data into a training set and a c hecking set (Figure 2). In this figure, y is a target and x is a v ariable. Subscripts *m* and *n* represent gas-in-oil and furfural compounds.

$$
\begin{array}{ll}
 & \begin{array}{cccccc} y & & & x & & \end{array} \\
\begin{array}{c} \text{Training} \\ \text{observations} \end{array} & \left[\begin{array}{c|cccc}
y_1 & x_{1,1} & x_{1,1} & \cdots & x_{1,m} \\
y_2 & x_{2,1} & x_{2,2} & \vdots & x_{2,m} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
y_{nt} & x_{nt,1} & x_{nt,2} & \cdots & x_{nt,m} \\
\hline
\vdots & \vdots & \vdots & \ddots & \vdots \\
y_n & x_{n,1} & x_{n,2} & \cdots & x_{n,m}
\end{array}\right] \\
\text{Test observations} &
\end{array}
$$

Figure 2: A sample of GMDH [20]

2) Set Up New Variables

Choose variable pairs from the independent variables ($x_1, x_2, \cdots, x_m$) which represent the contents of dissolved gas-in-oil or furfural compounds to generate combination units such as (x_{11}, x_{12}), (x_{21}, x_{22}), …, ($x_{\mathrm{nt},1}$, $x_{\mathrm{nt},2}$). In total, there are $C_2^m m(m-1)/2$ combination units. For each unit, a least squares (regression) polynomial is computed. Then, the life reduction of a transformer can be calculated by:

$$y = a + bx_i + cx_j + dx_i^2 + ex_j^2 + fx_i x_j \tag{1}$$

where, x_i ($i = 1, 2, \cdots, m$) and x_j ($j = 1, 2, \cdots, m$) are input variables, but $i \neq j$. Variable *y* is the proportional life reduction. Constants *a*, *b*, *c*, *d*, *e*, and *f* are regression coefficients.

From the observation dataset (x_{11}, x_{12}), (x_{21}, x_{22}), …, ($x_{\mathrm{nt},1}$, $x_{\mathrm{nt},2}$), polymomial (1) is the best representation of the relationship between responses *y* and inputs *x* of the training data. By inputting the observation data set into the polynomial a new variable set $Z_1^1 = (x_1, x_2)$, $Z_2^1 = (x_1, x_3)$, …, $Z_{C_2^m}^1 = (x_{m-1}, x_m)$ is generated.

3) Select Optimal Variables for Each Layer

If layer *k* has *q* input variables, layer *k*+1, will generate C_2^q input variables. In the long-term, numerous variables will reduce computation efficiency. To avoid adverse variables and obtain the best result, optimal variables are chosen as the input to the next layer. The variables are optimized in terms of the minimum Root Mean Square (RMS) which is calculated using:

$$r_i = \left[\frac{\sum_{t=1}^{n} (y(t) - Z_i^k(t))^2}{\sum_{t=1}^{n} (y(t))^2} \right]^{1/2} \quad (2)$$

r_i : *i*-th of RMS in layer *k*.

$t = 1, 2, \ldots, n$ is the number of data.

$y(t)$: the observational value of group t.

$Z_i^k(t)$: the i-th output value of group t in layer k.

There are two ways to select the variables. If the RMS is less than a predefined threshold r, the regression equation of this combination is selected. Then, arrange all the variables in a layer in an ascending order according to their RMS, and select the predefined number of new variables.

4) *Output the Optimal Model Structure*

The output is determined by comparing the two minimal indicators, $R_{\min}$, of two sequent layers. If the minimal indicator of a layer is greater than that of its previous layer, then stop adding layers and output the RMS error as the model outcome.

IV. CASE STUDY

This chapter will use both the internet and manual entry to upload data to the system. The data are obtained from the real-time monitoring equipment and sampling. The analysis of the key parameters are presented and the use of the intelligent maintenance assessment module is discussed. Finally, the sampling data from the study cases are input into algorithms to calculate the winding hot-spot temperatures and lifetime impairment as well as the lifetime impairment base on GMDH. The two results provide complementary information. The following sections will describes the application and results of each model.

A. The Case Background

In this study, the data collected are from 161 kV oil-immersed power transformers with real-time monitoring equipment used by a manufacturing plant in Taoyuan, Taiwan. The transformer has three fans, five thermometers and launched in 1996. The real-time monitoring devices monitor installed voltage, current, ambient temperature, oil temperature, and humidity which helps managers monitor real-time data transmittal through network cables to the Intelligence Maintenance Recommendation Platform.

B. Trend Analysis

Past data including voltage, current, loading and oil temperature are used to predict observed phenomena. The facility managers select specific objectives and times to determine whether there is the exception to the data distribution. According to the rising or falling trends recorded on the chart, high loading and high oil temperatures can be detected. Preventive measures are then taken to reduce the probability of the accident and avoid transformer damage.

C. Dissolved Gas-in-oil Analysis

According to the gas-in-oil diagnostic results, the equipment managers can predict abnormal conditions. The manager can add, modify, and delete the gas-in-oil data using the data management model. After completing data entry, the manager performs the numerical analysis [23] to generate a sampling data analysis report. The numerical analysis includes the Doernenburg, Rogers and Duval Triangle diagnosis methods. Sometimes managers can not determine the most probable fault even with the results derived from the three diagnostic methods. Lin [24] proposed a fault diagnosis method based on hybrid fuzzy dissolved gas analysis. Using the fuzzy theory to integrate diagnostic methods, more accurate results can be achieved. Wang and Chan [25] have also used neural networks to determine the cause of malfunction for oil-immersed transformers. The purpose is to find the failure factors quickly and resolve conflicting data.

D. Analysis of Remaining Life

Equipment managers assess the remaining life of a specific transformer in order to replace or discard it. The remaining life information helps avoid risks and losses caused by abnormal shutdown or failures. Because there are different assumptions and limits to the two assessment methods, this platform provides the two sets of result for complementary and comparative analysis.

We expect that if machine damage is serious, the lifetime impairment predictions can reduce possible losses. The next part of this discussion describes the GMDH remaining life assessment model for large-size oil-immersed transformers commonly used in electrical power plants.

The first step of GMDH is to enter the selected data for model training. In this research, we use 1 to 100 as the data modeling range. The 2-FAL is used to evaluate degree of polymerization of insulating paper and life of impairment assessment as proposed by Stebbins et al. [13] to calculate the lifetime impairment ratio and substitute for the real data as the modeling output value. After calculation of the output values, the next process is to select the variables for modeling. In this research we use oxygen, nitrogen, carbon dioxide, carbon monoxide, hydrogen, methane, ethane, ethylene, acetylene, the gases dissolved in the oil, 2-furfural, 2-furfuryl alcohol, 2-acetyl furan, 5-methyl-2-furaldehyde, 5-Hydroxymethyl-2-Furaldehyde, the total concentration of furfural as the input variables, and the ratio of life impairment as the output target. After inputting the selected variables, the next process is to set the required parameters information for the GMDH model. There are three parameters to set:

1) *The Maximum Layer for GMDH Modeling*

The maximum layer for GMDH modeling refers to the maximum number of layers. Usually, the number is set at three to five layers for best results. If the maximum layer is reached and the program does not converge, the minimum value of root mean square is used as the output result. If the user cannot determine the maximum layers for the GMDH model, then the optional default check bottom is select.

2) The Expansion Degree of Each Variable

The expansion degree of each variable refers to the variable dilation degree for each layer. The number 0 means that the total variables of each layer and the number of selected variables for modeling is the same and will not increase in each layer. The number 1 means the variable will double expansion in the next layer. For example, if the total variable is 16 in the first layer, then the modeling process going into the second layer will increase the variables to 32, and so on. The selected expansion degree is 1 in this research.

3) The Maximum Storage of Variables

The maximum storage of variables refers to the maximum temporary storage capacity in the computing layer. The input value must be at least greater than or equal to the total input variable and the setting number is base on computer performance. We used 1000 to be the maximum storage capacity.

However, we compare the storage capacity of 1000 and 5000 and evaluate the average error results. The outcome shows the smaller value is feasible for storage and requires less computing time.

Table 1 is the lifetime impairment assessment modeling results and error. The input variables in the established model selected by the system are nitrogen, carbon dioxide, carbon monoxide, the gases dissolved in the oil, 2-furfural, 2-furfuryl alcohol, 2-acetyl furan, 5-methyl-2-furaldehyde, 5-Hydroxymethyl-2-Furaldehyde, and the total concentration of furfural. The standard deviation (SD) is 0.059 and the root mean square error (RMSE) is 0.242 for the learning data set. The testing data set yields 0.045 as SD and 0.213 as RMSE. The results have shown very small errors as the lifetime impairment assessment model.

Table 1 Lifetime impairment assessment modeling errors based on GMDH

	Learning data (A)	**Testing data (B)**	**Total data (A)+(B)**
No. of Cases	70	30	100
SSE	4.098	1.37	5.469
Standard Deviation	0.059	0.045	0.055
RMSE	0.242	0.213	0.235

Figure 3 s hows the inaccuracy between the target and forecast values for the users to quickly interpret the correctness of the model. The lifetime impairment assessment model based on GMDH is validated using 191 samples of dissolved gas-in-oil and furfural from 40 transformers with satisfactory results.

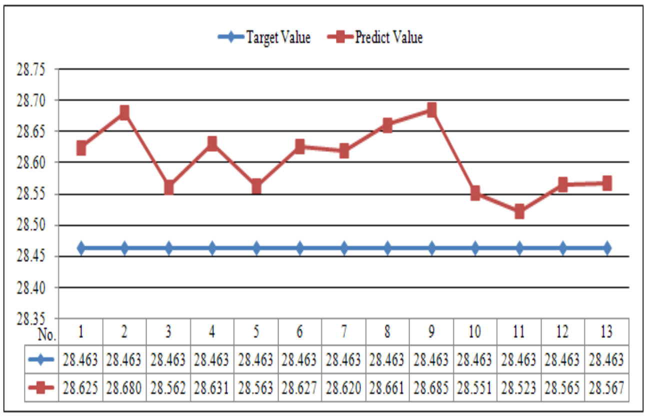

Figure 3 The deviations between the target and forecast values are small over 6-year of data tracking

V. CONCLUSION

An intelligence maintenance recommendation platform is designed and developed based on the real-time monitoring information from oil-immersed transformers. This platform integrates fault diagnosis and lifetime impairment assessment. The platform generates statistical reports and recommended maintenance strategies for managers to effectively and rapidly interpret transformer conditions and determine whether to maintain or replace the device. The platform provides three numerical analysis approaches, including Doernenburg, Rogers, and Duval Triangle methods, to simplify problem analysis. The lifetime impairment assessment is developed using Group Method of Data Handling (GMDH) approach to compute the transformer's remaining life. The proposed GMDH approach provides valuable prediction reference to the decision makers in addition to the traditional IEC standard life cycle assessment. The intelligent and visualization platform helps managers monitor the real-time asset conditions and update maintenance and procurement plans for transformer repair and replacement.

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