

POWER TRANSFORMERS CONDITION MONITORING USING DISSOLVED  
GAS ANALYSIS AND HIDDEN MARKOV PREDICTION MODEL

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To my beloved family

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## **ABSTRACT**

The reason of the power transformer (PT) monitoring is to prevent the failure of the PT. There are many methods to detect the failure of the PT. The methods include Conventional Monitoring System (CMS), Polarization Depolarization Current (PDC) Analysis, and Hidden Markov Model (HMM). The CMS gives the current condition of PT but it cannot give reliable failure prediction. The PDC involves complicated setup at site and the measurement is done when the PT is off line (shutdown) which is not preferable. HMM is a prediction model based on dissolved gas analysis (DGA) database. Its accuracy is believed to be further improved when more DGA data are available with the passing of time. The main focus of this project is to obtain the PT failure time estimates with an error of less than or equal to 10%. Mathematical models were used to predict the PT condition at several stages by knowing the current DGA data. Result shows the accuracy of 90% in transformer level prediction, means that 9 accurate results out of 10 transformers tested. The technique can be used to predict the transformer deterioration level and to prevent transformer failure which can lead to tremendous losses to company. The result will assist the maintenance personnel to make various maintenance decisions with cost effective way.

## ABSTRAK

Pengubahkuasa (PT) pemantauan adalah untuk mencegah kegagalan PT. Terdapat banyak kaedah untuk mengesan kegagalan PT. Kaedah-kaedah ini termasuk Sistem Konvensional Pemantauan (CMS), Polarisasi Depolarization Semasa (PDC) Analisis dan tersembunyi Markov Model (HMM). CMS memberikan kita keadaan semasa PT tetapi tidak boleh memberi kegagalan ramalan dipercayai manakala PDC melibatkan persediaan rumit di tapak dan pengukuran dilakukan apabila PT adalah di luar talian (penutupan) yang tidak ada lebih baik. HMM adalah model ramalan dengan mengumpul DGAs sebagai pangkalan data, ketepatan boleh dipertingkatkan lagi apabila pengumpulan data lebih banyak dilakukan. Walau bagaimanapun, kaedah yang lebih sempurna supaya ketepatan bertambah baik HMM tidak dibincangkan banyak. Oleh itu, untuk meningkatkan ketepatan ramalan merupakan fokus utama dalam laporan ini (sasaran ralat  $< 10\%$  daripada kegagalan masa anggaran). Lagipun, model matematik digunakan untuk meramalkan peringkat PT dengan mengetahui DGA semasa dibina dan ini adalah kaedah baru yang tidak pernah dibincangkan di dalam kertas lain. Keputusan menunjukkan ketepatan 90% dalam ramalan tahap pengubah, bermakna bahawa 9 keputusan yang betul daripada 10 pengubahkuasa yang diuji. Teknik ini boleh digunakan untuk meramalkan tahap kemerosotan pengubah dan untuk mencegah kegagalan pengubah yang boleh menyebabkan kerugian besar kepada syarikat. Keputusan yang diperolehi boleh membantu kakitangan penyelenggaraan untuk membuat pelbagai keputusan penyelenggaraan dengan cara kos efektif.

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## **CHAPTER 1**

### **INTRODUCTION**

#### **1.1 Introduction**

Power transformer (PT) is the most expensive and important item in any substation including a privately owned substation. Therefore a proper safeguard of the PT is a must in order to ensure the continuity of supply and hence the company's production and revenue generation. Transformer outages have a considerable economic impact on the operation of an electrical network and they affect company normal operation. Therefore, an accurate assessment of the PT condition is crucial in order to ensure its availability and reliability. With the increasing average age of the PT there is an increasing need to know the internal condition. The transformer cost is from a few hundred thousands to a few millions Ringgit Malaysian (RM). Furthermore, the failure of the power transformer can cost up to a few millions RM, and can highly affect the company performance. On average, the life of power transformer is between 25 to 30 years, and can be up to 60 years if proper condition monitoring and maintenance is being done. As transformer ages, the internal condition degrades thereby increases the risk of failure. Therefore, the prediction model which will be described in this report is used to prevent the transformer breakdown. The

conventional time based maintenance is really costly. In this work, the condition based approach is proposed. Three methods of condition based monitoring are discussed. These are the condition monitoring system(CMS), part..(PDC), and the Hidden Markov Model (HMM).In particular, the condition based approach using the Hidden Markov Model is implemented in this work.

This work describes a prediction model based on the dissolved gas analysis (DGA) data used as input data for the HMM to predict the deterioration level. 10 units of plant's PTs (130 MVA, 90 MVA, 70 MVA, 87 MVA, 67.9MVA, 35 MVA, 15MVA (2 units), 3 MVA and 2 MVA) were used to provide the input to the model. The necessary algorithm is designed and implemented. The result of the life prediction of the PT is calculated using the HMM system and then compared with the real deterioration level from the result of latest DGA readings. The accuracy of PTs life estimation is discussed and for further improvements.

The conventional condition monitoring of PTs [12] requires many set-up of sensors. The monitoring system tells us the abnormality of the PTs but cannot tell us the exact condition of the PTs and also the time to failure. The polarization and depolarization current (PDC) analysis only gives us the deterioration level when the PT is offline and it involves many setup for the depolarization current measurement. Therefore, not many companies practice this method. The HMM monitoring technique is to be discussed and implemented in this work. Two new items are introduced, which are to improve the prediction accuracy, and to give the immediate determination of deterioration level of PT. This improved model will be more practical since it provides accuracy of time to fail prediction and the actual condition of the PT at the time of oil sample taken.

The Hidden Markov Modeling [1, 2, 3] was initially introduced and studied in the late 1960s and early 1970s. Since then, this statistical method has become increasingly popular. The model is very rich in mathematical structure and hence it can form the theoretical basis for use in a wide range of applications. This model, when applied properly, works very well in practice for several important applications. Its applications include machine recognition of speech, *failure rate* calculation for power transformer, condition monitoring of oil-impregnated insulation paper, life estimation of electrical insulation in

rotating machine, and aging prediction for equipment followed by maintenance approach for cost saving purpose [6, 7].

The basic concept of the HMM is about a numerical statement model which is based on Markov chain and probability of state transition is developed. The hidden process which involve statistical approach which need to have 2 data inputs. First is the initial probability of deterioration level and second is the initial probability of Observation (DGA or TDCG). By having the current DGA (TDCG) result and the HMM calculation process is done, the deterioration level of PT is then obtained. This analytical approach assumes that if the equipment is not maintained, it will deteriorate in stages and will eventually fail. If the deterioration process is discovered earlier, proper preventive maintenance can be performed and this will restore the condition of the equipment.

To improve the HMM accuracy, more data need to be gathered. Therefore, in this work, 10 transformers were analyzed. The DGA data obtained are for 6 month intervals. The initial level of deterioration was obtained for each transformer. The transition matrix was then established. The probability for each transition in the transition matrix was calculated and then from the result obtained, the level of transformer degradation was estimated. The failure rate was then calculated. Next the time to transit to the next stage and the time to failure were estimated. For validation, the estimated results obtained were compared with the real state and condition of the power transformers. In this way, a continuous training of the model could be implemented by inputting recent data of transformer's DGA to this model.

The two key processes are: (a) Hidden Markov Chain - real status of the deterioration, and (b) Observation process –that is, observation obtained from monitoring and test.

This model is also characterized by **3 key parameters**:

- a. Markov transition matrix: state transition probabilities,  $A = \{a_{ij}\}$ ,  $a_{ij} = p(q_{t+1} = j \mid q_t = i)$ ,  $1 \leq i \leq N$ ,  
where  $q_t$  = the current state.
- b. Probabilities of getting an observation with a symbol under specific state  $B = \{b_j(k)\}$ ,  
 $b_j(k) = p\{O_t = v_k \mid q_t = j\}$ ,  $1 \leq j \leq N$ ,  $1 \leq k \leq M$ ,



where  $O_t$  = current observation.

c. Initial state distribution  $\pi = \{\pi_i\}$ , where  $\pi_i = p\{q_1 = i\}$ ,  $1 \leq i \leq N$ .

Using this model, we can obtain: (1) The time estimation of the power transformer to fail from the current level, and (2) The transformer's current stage or deterioration level. In short, the deterioration stage of PTs can be known by using the DGA track record with the help of the the proposed model algorithm. This model is good since it need not involve many tests (online and offline) to determine the transformer condition.

## 1.2 Problem Statement

HMM is the model that is widely used in many applications for event or condition prediction. Obtaining a high accuracy of the prediction is still a problem. Techniques to improve the model accuracy is discussed in this report. The DGA of the transformer is an input as observation and then the result would be the transformer deterioration level. A heavy mathematical calculations are needed to construct the mathematic model for the level transition process. Hence, accurate calculations are important to ensure the high accuracy of the prediction. This will enable the transformer maintenance to be carried out with minimum cost and will guarantee a zero breakdown of transformer.

## 1.3 Objectives

The main objective of the project is to eliminate the impact of a transformer failure without increasing the maintenance cost. The cost of power transformer maintenance will be reduced by implementing the prediction maintenance rather than conventional time based maintenance. The probability of the failure is estimated based on the DGA results. The time to failure is estimated and the proper maintenance planning will be initiated in order to prevent the failure of the transformer. The challenges of this project are the

heavy calculation needed in the HMM and then the deep understanding of this model also needed in order to construct the reliable model.

#### **1.4 Scope of Work**

(1) Data collection of DGA results for 10 Power Transformers in SSB (130 MVA, 90 MVA, 70 MVA, 87 MVA, 67.9MVA, 35 MVA (2 units), 3 MVA and 2 MVA). This data are observation data.

(2) To define the deterioration level (state) of transformer according to IEEE standard.

Level 1: Good

Level 2: Minor deterioration

Level 3: Major deterioration

Level 4: Failed

(3) From the data, to obtain the Probability of transition from level to level. (4 levels)

(4) To construct the HMM for Power Transformer Monitoring.

(5) By using HMM to obtain Probability of transformer failure.

(6) To compare the outcome of the model with the action level of transformer.

(7) Continue to fine tuning the system in order to achieve the minimum variance (10%).

(8) Using Excel to construct the system.

(9) From the above information, propose the maintenance time for each transformer.

## **1.5 Project Organization**

This project is represented by five chapters as below:

Chapter 1: Introduction to this project is being discussed. The problem statement, objectives, scope of works and project outlines is elaborated.

Chapter 2: Discussion about the HMM and others method in power transformer monitoring system. This chapter review other researchers' works and comparison is done.

Chapter 3: The methodology is being used in this project is explained. The flowchart and mathematic calculation are presented.

Chapter 4: This chapter is the results and discussion obtained in this project which is HMM prediction and transformer actual deterioration level.

Chapter 5: The last chapter is about the conclusion of this project and the future possible works which can be done to improve the HMM prediction accuracy.

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