MARKOV MODELS & NEURAL NETWORKS FOR FAILURE ANALYSIS OF POWER TRANSFORMERS

Mohammed Abdul Rahman Uzair [1], Dr. Basavaraja Banakara [2]

[1]*Research Scholar, Department of EEE, GITAM University, Hyderabad, INDIA.*

[2]*Professor and Head, Department of EEE, University BDT College of Engineering, Davanagere, Karnataka, INDIA.*

ABSTRACT: **In the proposed paper, we have presented two types of power transformer failure analysis tests. The methods are Hidden Markov Model concept and Artificial Neural Networks approach. Hidden Markov Model concept can be used to obtain the failure probability percentage of transformer through a MATAB program that was designed here. Artificial Neural Networks criteria was utilized for considering the key gas concentration ratios to analyze corresponding faults. In our proposed paper, the application of these methods was demonstrated on three power transformers from three substations spread across the states of Telangana and Andhra Pradesh, India. The results of methods we utilized prove that the three transformers were under three different conditions i.e., healthy, moderately deteriorated and extensively deteriorated conditions.**

Keywords: **Power Transformers, Hidden Markov models, MATLAB, Artificial Neural Networks.**

I. INTRODUCTION

Power transformers are responsible to a large extent for the power flow, power system efficiency and hence power transfer capability of large power systems. Power transformer failures lead to power supply interruptions in developing nations like India. Different techniques have been designed to nullify them.

In the proposed paper, we try to illustrate two methods to monitor a given power transformer's performance so as to get a first hand idea on its condition and appropriate preventive/maintenance steps can be undertaken.

The first one is Hidden Markov Model concept. In our paper, we implement this concept through a MATLAB program to get the failure probability percentage of the transformer and hence to monitor its condition.

The second one has application of Artificial Neural Networks (ANN) through IEC-599 Standard ratio method for identification of the most probable fault that has occurred in the transformer.

II. HIDDEN MARKOV MODELS

Markov Model is the one wherein the state is directly visible to the user and the state transition probabilities are the only parameters. However, a 'Hidden Markov Model' has state not directly visible i.e., the state is "hidden" and output, which is dependent on the state, is visible. The state sequence through which the model passes is 'hidden' and not the parameters of the model. Even when the parameters are exactly known, the model is still 'hidden' [1].

A) *Architecture Of A Hidden Markov Model*

General architecture of an HMM is shown in the **Figure1**. The random variable 'x(t)' is the hidden state at time 't' i.e., 'x(t)' ∈ $\{x_1,x_2,x_3\}$. The random variable 'y(t)' is the observation at time 't' where 'y(t)' ∈ $\{y_1,y_2,y_3,y_4\}$. The arrows denote conditional dependencies. The conditional probability distribution of the hidden variable 'x(t)' at time 't' depends only on the value of the hidden variable x(t−1) and the values at time (t−2) and before have no effect. This is called the 'Markov property'. Similarly, the value of the observed variable 'y(t)' only depends on the value of the hidden variable 'x(t)' (both at time 't').

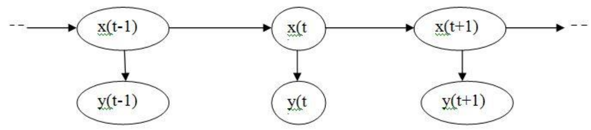

Figure1: General architecture of HMM

B) *Application Into The Fault Diagnosis Field*

The Fault Classification:

Although the method based on the dissolved gases analysis has some characteristics which indicate that identification method and is simple with fault classification result being explicitly specific, yet the classification and boundary of this method is over-absolute in practice. There still exist some mistaken phenomena which include: (1) Many compound fault problems aren't still solved carefully in actual such as electric discharge merge overheat etc, and (2) There exit some overlap distribute phenomena in the ratio boundary adjacent. Therefore, there are still many misjudges, lacking judges or non-judging cases during the actual fault diagnosis. The occurrence probability of these cases is relatively small and will be not considered when large quantity power transformers are counted and analyzed. But, these cases shouldn't be ignored and the DGA method should be improved for each power transformer. Each ratio in the new IEC three ratios method has different space interval. Based on the data statistics for large quantity power transformers with fault and referenced to some relative classification methods, the fault pattern for power transformer is classified as seven types. They are normal, overheat under moderate or low temperature (not more than 700˚C), overheat under high temperature (more than 700˚C), discharge under low-energy, discharge under high-energy, discharge under low-energy merge overheat, discharge under high-energy merge overheat.

ISSN: 2278 – 7798

Characteristic Variables Determination:

The purpose that some useful information obtained from the DGA data is to proceed for the pattern identification. The gas ratio selection and the characteristic dimensional will determine the fault classification correctness to some degree. There are several useful characteristic gases to judge oil filled transformer inner faults: hydrogen, methane, ethane, ethane, acetylene, ethylene, carbon monoxide and carbon dioxide. However, because of the easy presence of carbon dioxide in the air and insensitiveness to the faults, carbon dioxide shouldn't be considered as a fault characteristic gas. When some latent faults on power transformer occur, the carbon monoxide gas density may be much more than that of other characteristic gases. It will have an effect on the output probability computation in HMM model building and pattern classification for the other characteristic gases produced. In order to simplify problems and combine the actual condition for HMM model building and fault classification, there are five gases selected. They are hydrogen, methane, ethane, ethylene and acetylene. Carbon monoxide is considered as one of the characteristic gases to measure the power transformer running state. Now, the characteristic gas vector quantity composed of Dissolved Gas Analysis(DGA) data can be shown as $X = [H_2,CH_4,C_2H_6,C_2H_4,C_2H_2]$.

HMM Training and Fault Diagnosis Model Library Establishing:

HMM is trained as a representative of the power transformer normal working condition to the power transformer fault diagnosis. For all possible occurrence fault patterns, the HMMs are trained and a fault diagnosis model library is prepared. In order to judge a characteristic gas attribute to which types of fault, the signal must be preconditioned, and then compute each model's output probability in fault model library, compare all probabilities, take out the maximal output probability model and make the final fault decision. The output probability computation can be realized by the forward-backward algorithm or Viterbi algorithm. There are four hidden states to simulate the power transformer running pattern during HMM model building and it is assumed that the HMM model is a left-right type and the initial probability distribution vector quantity is $\Pi=[1,0,0,0]$. The hidden states can be denoted by the circle graduation with digitals shown in the **Figure2**. The arrows show the inter-dependency of variables and the symbols up the arrow show the state transition probabilities. As they reside in the state, each state can observe some vector quantity sequence, and O1,O2,...,OT, are all expressed as variance observed value vector quantities.

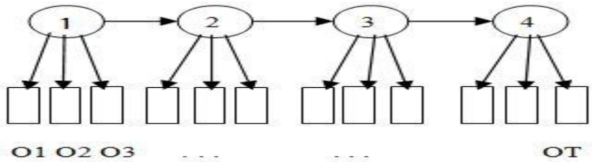

Figure2: HMM training and fault diagnosis model library establishing

HMM Training Process:

Once the HMM initial model is established, the training of HMM can be obtained by the iterative computation using the recurrence-thought Baum-Welch algorithm. The logarithmic value of maximum likelihood estimated value will be increasing till the convergence error and end since the iterations increase in HMM. Training of HMM has rapidly leaning performance and would have reached the convergence error in several steps domain in general. The important outputs after model training are state transition probability matrix and observable value probability matrix. The five fault patterns that include normal, overheat under moderate or low temperature, overheat under high temperature, discharge under low-energy, discharge under high-energy are modeled respectively by HMM. Each model training iterative curve shows that HMM has strong learning ability.

HMM Fault Diagnosis:

This is used for classification. Different fault characteristic patterns should build HMM, and the characteristic gas observable value can be used to quantify the sequence at fault classification. The probability '$P(O|\lambda)$' is calculated and reasoned by the forward-backward algorithm or Viterbi algorithm, then the probability output result is compared and the decision is made by the maximal output. For example, if 'λ_i' output probability is at the most, the fault pattern 'ω_i' will be judged. The quantification sequence for the characteristic gases observable vector quantity given by $X = [H_2,CH_4,C_2H_6,C_2H_4,C_2H_2,CO,CO_2]$ will be used as the input vector quantity, and the fault is classified by the built-in HMM. There are two types of outputs for HMM classification. The first one is HMM export logarithmic likelihood probability computation result. Another is the fault possibility corresponding to each of fault modes.

Fault diagnosis system design:

The system architecture includes four parts: data collecting and handling module, data display in real-time and monitoring module, data store and inquiring module, HMM model library and intelligent fault diagnosis module. The overall frame for the diagnosis system is as shown in the **Figure3** below.

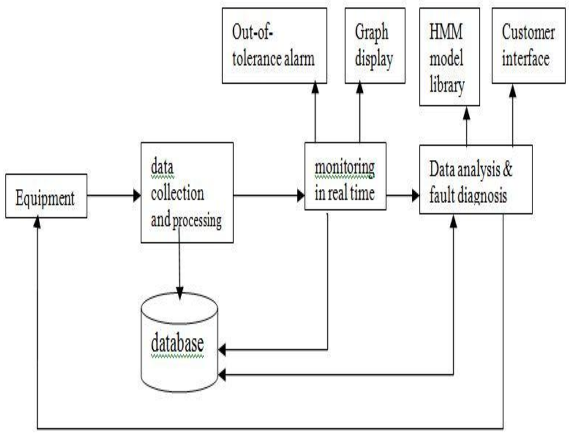

Figure3: The overall frame for the diagnosis system

The main steps in the frame for the HMM process include:

Fetch data from the data collecting card and proceed to dispose.

Monitor the characteristic gas data in real–time and display graph, give alarm when the data is out-of tolerance.

Finish the interactive operation between the application program and the data base; realize the data store and transmission.

HMM fault diagnosis module can diagnose the equipment fault when it occurs and can combine with the other fault diagnosis methods to proceed to synthesis judge.

ISSN: 2278 – 7798

The HMM method is thus used to get the fault diagnosis i.e., fault probability of the transformer with the help of MATLAB coding on a computer.

Flowchart for Hidden Markov Models Program [6]:

A flowchart for the fault diagnosis using HMM is shown in the **Figure4** below.

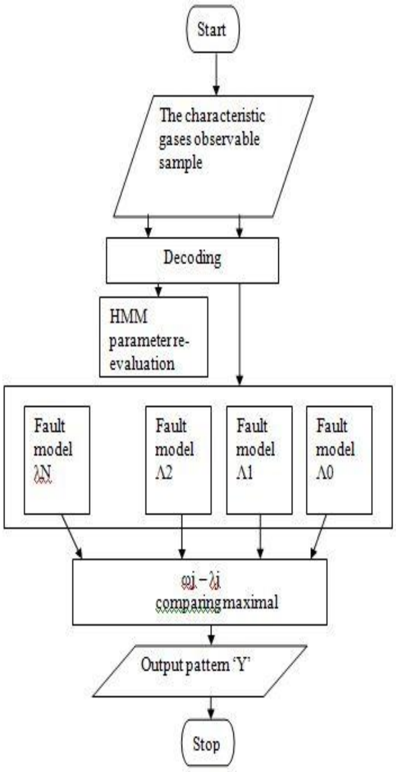

Figure4: Flowchart for HMM program

Description of the flowchart:

The characteristic gases from the power transformer oil sample are taken. Decoding is done for them so as to be understandable to the system.

Fault models from the fault model library are compared with the input gas concentrations.

The fault model which is most similar i.e., having the maximal output with respect to the input, is considered and is given as output.

IV. ARTIFICIAL NEURAL NETWORKS APPROACH

For the application of Artificial Neural Networks concept to the power transformer failure analysis, after a careful study of the various available probability computation methods, one has been picked for consideration here.

Rogers, Dornenberg and IEC-599 are the most commonly used ratio methods. They employ the relationships between key gas contents. The key gas parts per million (ppm) values are used in these methods to generate the specific ratios which represent characteristic failures in the power transformer [2].

The IEC method uses gas ratios that are combinations of key-gas ratios C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6.

The three gas ratios and corresponding to the suggested fault diagnosis in the power transformers as per the IEC-599 Standard can be summarized as in the **Table-1** below. When key-gas ratios are in the specified limits, incipient faults shown against the ratio values can be expected in the transformer.

Table-1: Gas ratios and corresponding faults in transformers as per IEC 599

Fault type	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
Partial Discharge (PD)	< 0.1	< 0.1	< 0.2
Discharge under low energy (D1)	> 1	0.1 – 0.5	> 1
Discharge under high energy (D2)	0.6 - 2.5	0.1 - 1.0	> 2
Fault at low temperature (T1)	< 0.1	> 1	< 1
Fault at low to medium temperature (T2)	< 0.1	> 1	1 – 4
Fault at high temperature (T3)	< 0.1	> 1	> 4

V. OIL TESTS ON A SAMPLE

Oil samples were collected from power transformers located at three different substations namely 132kV Vijayawada substation (Andhra Pradesh), 220kV Chandrayanagutta substation (Telangana) and 132kV Port substation (Andhra Pradesh). MATLAB program was designed and run for getting the failure probability percentages for Hidden Markov Models method while key gas ratios were computed to get the results for Artificial Neural Networks concept.

The results are described in the following Tables.

Case-1: Power Transformer Oil Sample Test Results under Healthy Condition:

An 8 year old 132/33kV, 20 MVA power transformer located at 132kV Vijayawada substation was considered as Case-1 [3].

For the Hidden Markov Model (HMM) analysis results, **t**he input characteristic gases observable vector quantity is X=[3.96,1.52,8.57,0.47,0.43], HMM classification output result is showed in **Table-2**, where the identification results are for discharge under high-energy, and the fault occurrence probability is **52.32 %**.

ISSN: 2278 – 7798

Table-2: HMM Classification Output Results

Output	Normal	Overheat under moderate or low temperature	Overheat under high temperature	Discharge under low energy	Discharge under high energy
Logarithmic likelihood probability	infinity	6.93e-1	3.43e+1	1.5e+1	2.5e+0
Fault possibility (%)	8e+0	6.31e+0	**5.232e+1**	5.9e+1	0.9e+2

Remarks: The fault occurrence probability is '**52.32%**'.

The Artificial Neural Network application results are as shown in the **Table-3** below [4].

Table-3: Artificial Neural Networks approach results (Healthy condition)

Ratio of gas	Ratio value	Fault type (as per IEC-599)
C2H2/C2H4	0.05017	No fault condition!
CH4/H2	0.3838	
C2H4/C2H6	18.2340	

As per the above table, the ratio values are out of range compared to those considered for fault conditions. As per IEC- 599, the power transformer is healthy.

Case-2: Power Transformer Oil Sample Test Results under Moderately Deteriorated Condition:

A less than 6 year old 220/132kV, 100 MVA power transformer located at 220/132/33kV Chandrayanagutta substation was considered as Case-2.

For the Hidden Markov Model (HMM) analysis results, **t**he input characteristic gases observable vector quantity is X=[42.54,12.62,10.17,2.85,25.63]. HMM classification output result is shown in **Table-4**, where the identification results are for discharge under high-energy, and the fault occurrence probability is **62.059 %**.

Table-4: HMM Classification Output Results

Output	Normal	Overheat under moderate or low temperature	Overheat under high temperature	Discharge under low energy	Discharge under high energy
Logarithmic likelihood probability	Infinity	1.16e+2	5.97e+1	3.45e+1	6.63e+2
Fault possibility (%)	8.6e+1	5.13e+1	**6.2059e+1**	2.52e+1	3.60e+2

Remarks: The fault occurrence probability is '**62.05%**'.

The Artificial Neural Network application results are as shown in the **Table-5** below.

Table-5: Artificial Neural Networks approach results (Moderately deteriorated condition)

Ratio of gas	Ratio value	Fault type
C2H2/C2H4	2.52015	Discharge under low energy (D1)
CH4/H2	0.29666	
C2H4/C2H6	3.56842	

As per the above table, the ratio values when compared with IEC- 599, indicate that the power transformer is experiencing Discharge under low energy i.e., the power transformer is moderately deteriorated.

Case-3: Power Transformer Oil Sample Test Results under Extensively Deteriorated Condition:

A 5 year old 15MVA power transformer of NGEF make located at 132kV Port substation was taken as Case-3.

For the Hidden Markov Model (HMM) analysis results, **t**he input characteristic gases observable vector quantity is X=[235.07,49.07,117.4,15.7,62.9]. HMM classification output result is shown in **Table-6**, where the identification results are for discharge under high-energy, and the fault occurrence probability is **72.66 %.**

ISSN: 2278 – 7798

Table-6: HMM Classification Output Results

Output	Normal	Overheat under moderate or low temperature	Overheat under high temperature	Discharge under low energy	Discharge under high energy
Logarithmic likelihood probability	Infinity	5.65e+0	2.10e+1	1.13e+1	5.79e+1
Fault possibility (%)	4.8e+1	2.03e+1	**7. 266e+1**	1.50e+1	1.65e+2

Remarks: The identification results are overheat under high temperature (i.e., the thermal fault), and the fault occurrence probability is '**72.66%**'.

The Artificial Neural Network application results are as shown in the **Table-7** below.

Table-7: Artificial Neural Networks approach results (Extensively deteriorated condition)

Ratio of gas	Ratio value	Fault type
C2H2/C2H4	0.53577	Fault at high temperature (T3) i.e., Thermal fault
CH4/H2	0.208746	
C2H4/C2H6	7.4777	

As per the above table, the ratio values when compared with with IEC- 599, indicate that the power transformer is extensively deteriorated.

VI. CONCLUSION

In the proposed paper, we have explained two methods of determining the power transformer failure condition for undertaking maintenance steps. The first one, Hidden Markov Models concept was used to compute the failure probability percentage of power transformers. The second one, Artificial Neural Networks concept, was used to establish the expected faults in a power transformer.

As case studies, transformer oil samples from three substations were collected and tested for analyzing the failures. Accordingly, the transformer oil samples were found to be in three different conditions namely healthy, moderately deteriorated and extensively deteriorated conditions. The above mentioned tests were conducted on these oil samples.

ACKNOWLEDGMENT

Mohammed Abdul Rahman Uzair is thankful to his research supervisor, Dr. Basavaraja Banakara, for his guidance and support in coming up with an innovative and competitive research work. He is also thankful to the GITAM University for providing a favorable and competitive environment that helped him to grasp innovative ideas.

REFERENCES

[1] Rabiner L.R., "A tutorial on hidden Markov models and selected applications in speech recognition," Proceedings of IEEE, vol. 77, no. 2 pp.257— 286, 1989.

[2] Seifeddine S, Khmais B and Abdelkader C, "Artificial Intelligence Tools Aided-decision for Power Transformer Fault Diagnosis", International Journal on Computer Intelligence (IJCI), volume 38, no. 3, 2012.

[3] Uzair MAR, Mohiuddin M and Shujauddin MK, "Failure Analysis of Power Transformers", International Journal of Emerging Technology and Advanced Engineering (IJETAE) volume 3, no. 9, 2013.

[4] Uzair MAR and Dr. Basavaraja B, 'DGA, Wavelet & ANN Techniques For Failure Analysis of Power Transformers', International Journal of Science, Engineering and Technology Research (IJSETR), Volume 4, Issue 10, October-2015.

Mohammed Abdul Rahman Uzair was born at Nalgonda near Hyderabad, India. He completed his B.Tech in Electrical and Electronics Engineering, from JNTU Hyderabad in the year 2003. He completed his M.Tech in Electrical Power Engineering, from JNTU Hyderabad in the year 2012. Currently, he is pursuing PhD from GITAM University, Hyderabad campus on the topic 'Failure Analysis of Power Transformers'. He is working as Associate Professor in the Department of EEE, Nawab Shah Alam Khan College of Engg & Tech, Hyderabad, since 2012. His fields of interest are Power Systems and Power Electronics. So far, he has published 9 papers in International Journals and 1 paper in a National Journal.

Dr. Basavaraja Banakara was born in 1970. He is Senior Member IEEE since2005. He obtained his B.Tech(EEE) degree from Gulbarga University and M.Tech from Karantaka University, India. He obtained his Doctoral program at National Institute of Technology, Warangal, India. He worked as a Lecturer in VEC, Bellary, Associate Professor at SSJ Engineering College, Mahaboobnagar, Professor EED at K L University, Guntur. He worked as Vice-Principal, Professor and Head in GITAM University, Hyderabad. Presently, he is working as Professor and Head, EEE Dept, University BDT College of Engineering (VTU), Davanagere, Karnataka. He has Published 8 International Journal papers, 21 International conference papers and 5 National conference papers. His areas of interest include power electronics and drives, FACTS Devices and EMTP applications.

ISSN: 2278 – 7798