Neuro Fuzzy System Based Condition Monitoring of Power Transformer

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Abstract: A power transformer is a static piece of apparatus with two or more windings. By electromagnetic induction, it transforms a system of alternating voltages and current into another system of alternating voltages and current of different values, of the same frequency, for the purpose of transmitting electrical power. For example, distribution transformers convert high-voltages electricity to lower voltages levels acceptable for use in home and business. A power transformer is one of the most expensive pieces of equipment in an electricity system. Monitoring the performance of a transformer is crucial in minimizing power outages through appropriate maintenance thereby reducing the total cost of operation. This idea provides the use of neural fuzzy technique in order to better predict oil conditions of a transformer. The preliminary phase is the first and most important step of a neural fuzzy modeling process. It aims to collect a set of data, which is expected to be a representative sample of the system to be modeled. In this phase, known as data processing, data are cleaned to make learning easier. This involves incorporation of all relevant domain knowledge at the level of an initial data analysis, including any sort of preliminary filtering of the observed data such as missing data treatment or feature selection. The preprocessing phase returns the data set in a structured input-output form, commonly called a training set. Once this preliminary phase is completed, the learning phase begins. This paper will focus exclusively on this second phase assuming that data have already been preprocessed. The learning phase is essentially a search, in a space of possible model configurations, of the model that best represents the power transformer testing values. As in any other search task, the learning procedure requires a search space, where the solution is to be found, and some assessment criterion to measure the quality of the solution.

Key-Word: Insulting Oil, Breakdown test, ANFIS, Fuzzy logic

1. Introduction

In power Transformer there are many factors, which play an important role in the service & failure of the Transformer. Mineral oils are used as insulating and cooling agents in transformers due to their good aging behavior and low viscosity. Their inservice characteristics are continuous varied with time having as a result the degradation of the insulation and the decrease of the residual operating time of transformer oil [1]. Not only the conduction part is affected but also there is an impact on insulating material, which causes the major failure of the system. At present large number of power transformer in operation have entered their oldest stages, and more attraction to the insulation condition is being paid. Nowadays economically reliable and effective power delivery is the primary concern all over the world. Therefore it is for a great importance to properly evaluate the ageing condition of an insulating material related to the transformer. Neuro-fuzzy is a reliable classification technique based on fuzzy and artificial neural networks (ANN) [2], [3]. Oil filled Transformer are widely being used in transmission & distribution system. Oil is subjected to the degradation because of the ageing, high temperature and chemical reactions such as the oxidation.Then the oil condition has to be checked regularly and reclaimed or replaced when necessary, to avoid the sudden failure of the transformer. It will be very desirable also if we can predict the transformer oil remaining lifetime, from time to time [4]. The properties of oil will be analyzed by various test such as Breakdown Voltage (V_b), Loss Factor ($\tan\delta$), Dielectric constant ($\in r$) and resistively (ρ) etc [5]. Moisture & oxygen causes the oil - paper insulation to decay much faster than the normal rate, form acid & sludge, settles steadily on winding & inside the structure causing transformer cooling to be less efficient. Accurate prediction is the most fundamental but not necessarily be the only objective in modeling. The model should serve as a good description of the data for enlightening the properties of the input-output relationship. The model should also be interpretable, so that the user can gain insight and understand the system that produced the data. In nearly all everyday systems, models are derived from two fundamental sources: empirical data acquired from observation and a priori knowledge about the system. Fuzzy sets are powerful tools for capturing such qualitative a priori knowledge [6]. Neural fuzzy modeling is the task of building models from a combination of a priori knowledge and empirical data. Normally, such a priori knowledge is used to define a suitable model structure; this model is then adapted such that it successfully reproduces the available empirical data. This adaptation step is often called learning. The main objective of neural fuzzy modeling is to construct a model that accurately predicts the value(s) of the output variable(s) when new values of the input variables are presented [7], [8]. Section-2 describes functional requirement, properties and breakdown test of transformer oil. The chemical and electrical tests have been performed on sampled oil for ageing analysis of power transformer. Section-3 describes overviews of Fuzzy logic, problem formulation and solution methodology. Section-4 describes Results and discussions. Section-5 gives conclusions.

2. Transformer Oil Treatment

One of the main insulators which are used in a transformer is oil. Oil serves the main function as well as coolant. Since the life of a transformer on the life of the oil, priority is given to the quality and stability of the oil. The oil filled transformer should have the following properties:-

Table1: Transformer oil properties

S. No.	Characteristics	Limit
1	Sludge value	120%
2	Acidity after oxidation (max) KOH	25 mg
3	Flash point	2940 F(146.10 C)
4	Viscosity at 700 F	37
5	Pour point	-250F
6	Specific gravity	No limit
7	Saponification value	1.0 mg KOH/g
8	Electric strength(1min)	40

REQUIREMENTS OF INSULATING OIL

The three main functional requirements of insulating oil are:

- To meet the **insulation function,** the oil has high dielectric strength and low dissipation factor to withstand electric stresses imposed in service.
- To meet **heat transfer and cooling function** the oil must have viscosity and pour point that are sufficiently low to ensure that the oil circulation is not impaired at the most extreme low temperature conditions for the equipment.
- To meet the **arc quenching function**, the oil requires a combination of high dielectric strength, low viscosity and high flash point to provide sufficient insulation and cooling to ensure arc is extinguished.

THE GENERAL REQUIREMENTS

- The **Breakdown Voltage** should be sufficiently high to provide dielectric strength to prevent oil under electrical stresses.
- The **Moisture content** of the oil must be low, otherwise the electric strength of the oil will be impaired and moisture will be absorbed in any insulating paper, reducing insulation life and increasing the risk of dielectric breakdown.
- The oil must have a low **Particle Size and Count** and low **fiber content** as the presence of such contaminants, especially in the presence of moisture, can considerably reduce the electric strength.
- The **Viscosity** of oil needs to be low enough to ensure the oil flows under all temperature (particularly low) conditions thus providing necessary cooling and arc quenching properties.

SAMPLING OF INSULATING OIL FOR TRANSFORMER

- Sampling should be performed on a sunny day. Do not sample when humidity is above 75%.
- The oil should be at least as wars as ambient temperature. Cold oil could condense moisture from humid air and give poor results.
- The oil sample should be obtained from the bottom drain valve. Do not attempt to sample if the transformer is under negative pressure.
- The sampling valve must be cleaned prior to sampling.
- Flush drain valve with sufficient oil to remove stagnant oil from the valve and drain pipe (1/2 to 1 gallon of oil).The oil sample must be representative, i.e., oil which is circulating within the transformer.
- Rinse the jar several times with the oil to be tested before obtaining the actual sample.
- Fill the 650 ml jar ¾ “from the tap to allow oil expansion or contraction.
- Fill out the information tag completely and attach it to the sampling bottle immediately following sampling.

BREAKDOWN TEST OF THE TRANSFORMER OIL

Breakdown test are normally conducted using test cells. For testing pure liquids, the test cells used are small so that less quantity of liquid is used during testing .The electrodes used for breakdown voltage measurements are usually spheres of 0.5 to 1 cm in diameter with gap spacing of about 100-200mm. The gap is accurately controlled by using a micrometer. Sometimes parallel plane uniform field electrode systems are also used. Electrode separation is very critical in measurements with liquids, and also the electrode surface smoothness and the presence of oxide films have a marked influence on the breakdown strength. The test voltages required for these tests are usually low, of the order of 50-100kV, because of small electrode spacing. The breakdown strengths and D.C. conductivities obtained in pure liquids are very high, of the order of 1MV/cm and 10^-18 to 10^-20 mho/cm respectively.

3. Neuro Fuzzy Modeling

Neuro-fuzzy systems are ideal candidates to fulfill analysis objectives. Adaptive neuro-fuzzy inference system (ANFIS) and hybrid fuzzy inference system (HyFIS) is the two most popular neuro-fuzzy connectionist systems that simulate a Sugeno and a Mamdani type FIS, respectively. Both algorithms have been validated on various data sets and were shown to possess good accuracy. However, they are not without their drawbacks in the condition based maintenance context as elucidated below.

Consider a domain described by a function y = f (x1, x2), a Mamdani type FIS in this domain would consists of rules of the form “IF x1 is low AND x2 is medium THEN y is high,’’ where low, medium and high are linguistic terms with functional forms like Gaussian, Sigmoid, etc., also known as membership functions. A Sugeno type FIS in this domain would consist of rules of the form “IF x1 is low AND x2 is medium THEN y = f1(x1, x2),” where low and medium are linguistic terms with functional context. The difference between the two FIS is the form of consequents.

In Mamdani type FIS the output membership function can be defined independent of the premise parameters; whereas in Sugeno type FIS each output membership function is a function of the inputs. ANFIS mimics a Sugeno type FIS. It is efficient for function approximation problems and is not particular useful in classification applications. Hence, it is not appropriate for diagnosis applications and the knowledge (rules) it extracts would be abstract for a domain expert as they are not entirely in a linguistic format. HyFIS, on the other hand, simulates a Mamdani type FIS which is universally applicable and hence can be used for diagnosis applications. However, it uses a defuzzification (process of generating crisp outputs from fuzzy outputs) strategy that restricts the output membership functions to assume a Gaussian functional form (with center and variance parameters). Although this does not hamper its ability to generate maintenance solutions, it is not possible for a domain expert to interact with the model in all situations (for instance, when output membership functions are non-Gaussian). Fuzzy neural networks can have fuzzy input and/or fuzzy weight. Different learning algorithms can be applied depending on the model.

Due to the complexity of the numerous phenomena, it is difficult to formulate a precise relationship relating the different contributing factors. This uncertainty naturally lends itself to fuzzy set theory. For this reason, most black box and gray box diagnostic techniques have used fuzzy logic to some extent. The knowledge of expert system has many uncertainties, and therefore fuzzy logic is employed. In this case, the neural network employs sampled learning to complement the knowledge-based diagnosis of the expert system. The two techniques are investigated are integrated by comparing the expert system conclusion with the neural network reasoning using a consultative mechanism. A block diagram for this type of hybrid system is given in figure1.

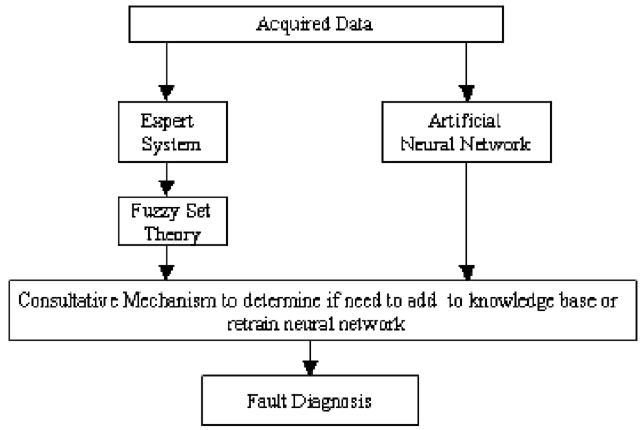

Figure 1: Strategy for combined fuzzy logic, expert system, and neural network

In this case fuzzy logic is implemented in coordination with neural network. The output of the neural network is numerical values between 0 and1, which are placed membership functions based on a set of fuzzy rules.

The idea of fuzzification of control variables into degrees of membership in fuzzy sets has been integrated into neural networks. See figure. If the inputs and outputs of a neural network are fuzzified and defuzzified, significant improvements in the training time, in the ability to generalize, and in the ability to find minimizing weights can be realized. Also, the membership function definition gives the designer more control over the neural network inputs and outputs. It is this technique that is implemented in this thesis for the diagnosis of the oil condition of the transformer.

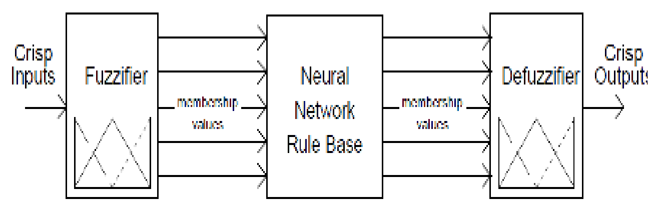

Figure 2: A fuzzy system with neural network rule base.

The fuzzy logic modeling and analysis has been carried out to get better asset’s remnant life estimation. Figure 3, 4 represents mamdani and sugeno FIS editor showing 2-input variables and 1 output variable, figure 5, 6 & 7 represents the mamdani FIS membership function plot of moisture, particle count input variables and condition (age) output variable, figure 8, 9 & 10 represents the sugeno FIS membership function plot of moisture, particle count input variables and condition (age) output variable, figure 11 and 12 represents the rule view of mamdani and sugeno type input and output variable.

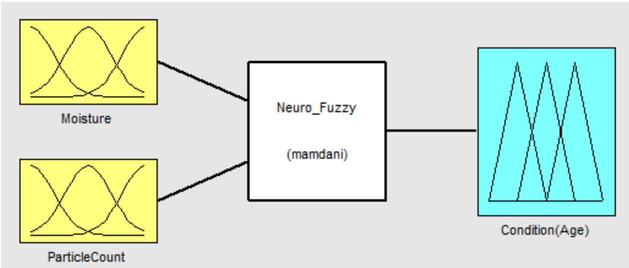

Figure 3: Mamdani FIS editor

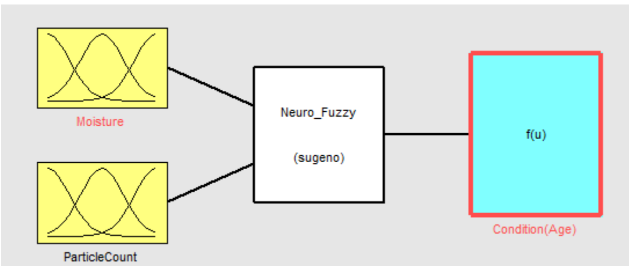

Figure 4: Sugeno FIS editor

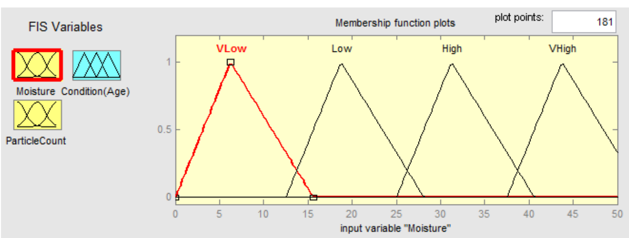

Figure 5: Mamdani FIS editor showing membership function plot of moisture

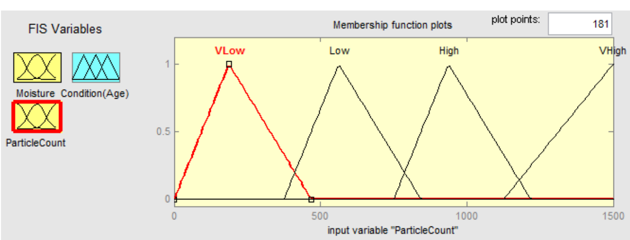

Figure 6: Mamdani FIS editor membership function plot of particle count

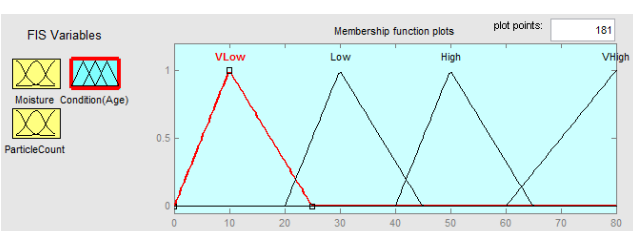

Figure 7: Mamdani FIS editor membership function plot of condition(Age)

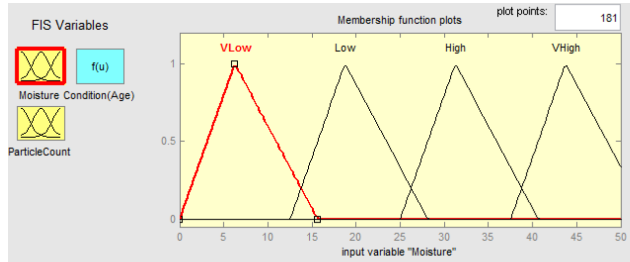

Figure 8: Sugeno FIS editor showing membership function plot of moisture

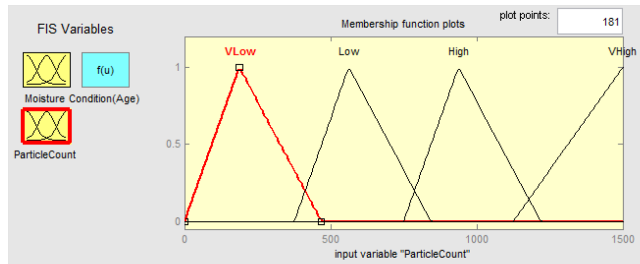

Figure 9: Sugeno FIS editor membership function plot of particle count

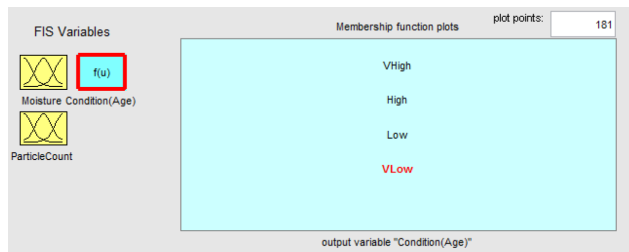

Figure 10: Sugeno FIS editor membership function plot of condition(Age)

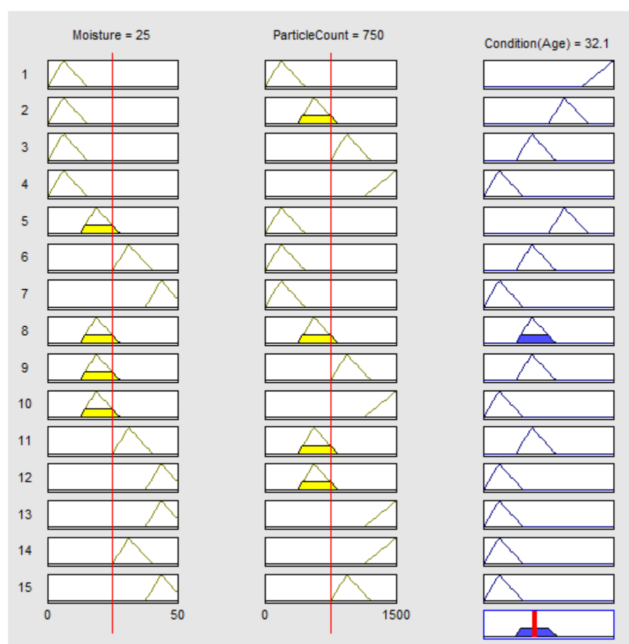

Figure 11: Rule view for final membership function-FIS(mamdani)

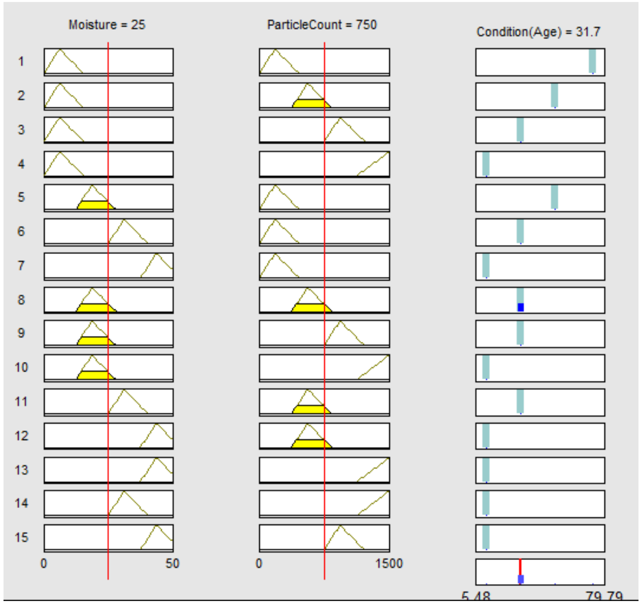

Figure 12: Rule view for final membership function-FIS (sugeno)

4. Results

Developed algorithms have been used to evaluate the condition of power transformer. The tests have been conducted on collected samples. In fuzzy system triangular membership function has been used. Condition (Age) of the transformer is evaluated using developed fuzzy logic algorithm and obtained results have been compared with well established BDV test on transformer oil for breakdown strength.

Command fis(sug)=mam2sugfis(mam), Generates a single output Sugeno-type fuzzy inference system. We are using mamdani type FIS for transformer oil analysis. Firstly we will select desired input variables and define the corresponding membership functions. Add fuzzy rules for the modeling system this will give the rule view and surface view of the model. By using the command *mam2sug* we can convert a non-linear system into linear or we can say sugeno type FIS. After designing the model and after defining fifteen rules for the system the results are obtained. Figure 3 shows a Neuro Fuzzy system with fifteen rules, two inputs and one output.

5. Conclusion

The model for condition monitoring of transformer presented here with the use of neuro-fuzzy logic controller. This method can be used for the various inputs and one output, strictly depends on the number of membership functions and their rule base and the type of the defuzzification method used. The oil must have a low Particle Size and Count and low moisture as the presence of such contaminants, can considerably reduce the electric strength. The model for condition of transformer presented here with the use of fuzzy logic controller. The fuzzy method has been proposed in this work due to its simplicity and accuracy.

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