Data Driven Condition Monitoring Model of Power Transformer for Diagnosing Incipient Faults in Smart City Network

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Abstract. Power transformers are an indispensable part of smart city infrastructure and one of the most expensive components of this kind of infrastructure. The insulation of the transformers is formed by mineral oil and cellulose, both of which can degrade due to multiple stresses (electrical/mechanical/thermal/chemical). This paper proposes a new computational model for asset decision making, taking into account several important variables such as dissolved gas analysis (DGA), water content, furan, interfacial tension, and degree of polymerization. Contour plots and surface viewers are also used to analyze different stresses on its insulating structure. Gas ratio techniques, Duval Triangle technique, Degree of polymerization and furans based paper deterioration, moisture and IFT based insulation degradation and other dissolved gas analysis based diagnostic procedures are used and its shows the higher accuracy analysis and efficiency for incipient faults diagnosis and analysis with AI based computational intelligence.

Keywords: *Power Transformer, Condition Monitoring, Data Analysis, Fuzzy Logic System, Smart City*

1 Introduction

Both paper and oil are indispensable elements of the dielectric insulation in power transformers. Power transformer insulation may deteriorate due to a variety of electrical, mechanical, thermal, and chemical stress that occur during operation [1-3]. And it can cause a series of internal faults such as cellulose overheating, winding circulating current, corona discharge, partial discharge, thermal hot spot and arcing etc., and in-tank tap changer deform. Continuous operation of the transformer breaks down both the solid and the liquid insulation and its dielectric characteristic. Several authors have contributed to the field of power transformer status monitoring and have discovered a variety of fault diagnostic techniques [4-8]. Subsequent paragraphs, however, are indented.

In this article, a AI based computational intelligence strategy that uses fuzzy logic controllers (FLC) is used in this study to manage the large asset like power transformer. In the suggested asset management paradigm, the few steps are followed. The initial phase entails the creation of intricate cognitive rules for identifying early defects. The second is processing a diagnosis result on the basis of a fuzzy ruler for decision and the third is testing insulation condition of a power transformer.

Ageing of oil and paper insulation: interpretation of incipient faults. The mechanism of the power transformer insulation degradation is a complicated topic to study. Transformer insulation degradation is caused by electrical, mechanical, thermal and chemical stressors. Condition-based assessment (CBA) recommendations state that prompt maintenance is required to avoid an early breakdown of the power transformer [9-13].

The core and windings take a real hit from stronger electrical stresses like lightning strikes or switching surges. These kinds of stresses speed up the aging of both solid and liquid dielectrics, whether they come from inside or outside the transformer.

When arcing occurs, overheating or early faults, they lead to the formation of all kinds of gases in the transformer oil: hydrogen, methane, ethane, ethylene, acetylene, carbon and various oxides [14-18]. The solid insulation decomposition causes a lot of losses and chemical contaminants like slurry and sludge. Pressboard, paper, clack bands and other solid insulation materials link the aging process with the liquid particles, hotspot temperature, Furan compounds, other foreign particles, water, acid compounds and BDV [19-23].

2 AI based computational intelligence to diagnose incipient faults in smart city network

Professor Lotfi Zadeh [14] first presented Fuzzy logic controllers (FLC) in 1965, and they have since expanded. Qualitative or linguistic data is used in the FLC algorithm. Impact of the FLC on the rule base is local. The rule base reflects the history of the data, its outcomes, and any required or anticipated actions for the next stage of the process. By definition, a membership function is given as μA : X→ [0, 1] for a fuzzy set A on the domain of discourse X, where each element of X is mapped to a value between 0 and 1 [15–17]. The degree of membership or membership value is a single parameter that refers to membership. Once the data processing is completed, the expert system is initially prepared with the aid of a MATLAB Simulink model.
Fig. 1 illustrates how this data is handled using a cognitive fuzzy logic technique after that fuzzy rules are employed for diagnosis prediction. To provide a complete diagnosis of the insulation status evaluation, the FLC-created improved expert model has been deployed with substantial potential incipient problems. The preparation of this decision-making model incorporates all of the crucial aspects related to paper and oil insulation.

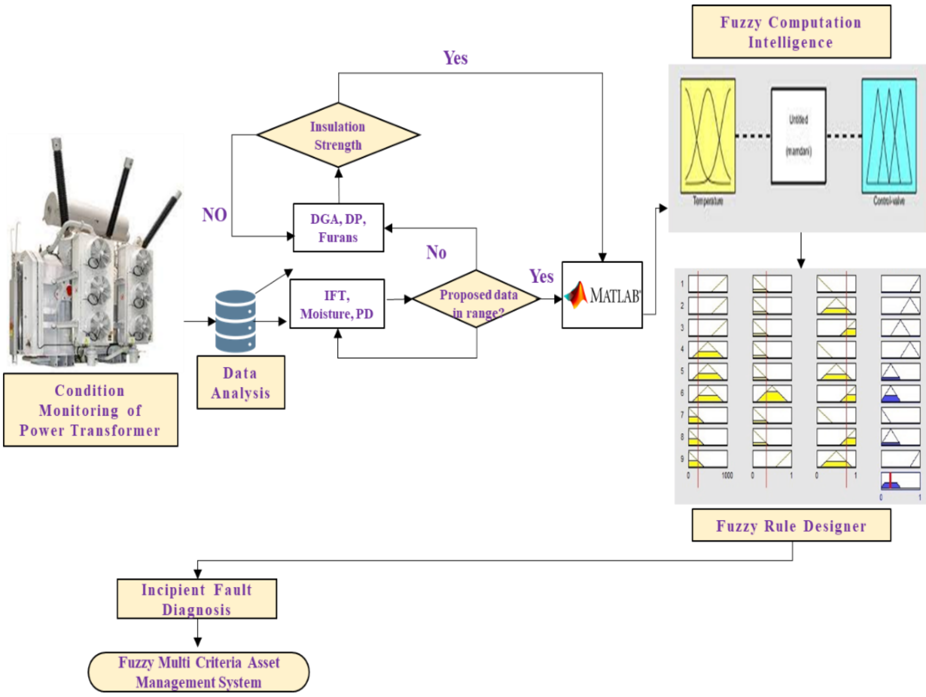

Fig. 1. Computational intelligence model of smart city power transformer

This methodology uses various physical, electrical, mechanical, electrical and chemical analysis parameters for fault diagnosis and interpretation. To further perform a thorough examination of insulation deformation, the MATLAB SIMULINK model was developed for fault detection and forecasting.

2.1 Fuzzy input processing for membership allocations

Fuzzification is the method of utilizing the necessary MFs to generate fuzzy values from precise inputs. The three inputs are denoted by a commonly used triangular (TMF) and trapezoidal (TRMF). TMF inputs with degree of membership function (DOM) are chosen using the following mathematical formulas related to equations (1) and (2), which are displayed in Fig. 4.

$$\mu_1(a)(z;p,q,r) = \begin{cases} 0, & (z \le p) \\ \frac{z-p}{q-p}, & (p \le z \le q) \\ \frac{r-z}{r-q}, & (q \le z \le r) \\ 0 & (r \le z) \end{cases} \quad (1)$$

In the present work, according to the MF, if x is between a and b, then its MV will be in the interval [0,1]. The value will be nearly 0 when x is close to a and nearly 1 when x is near b, and between b and c the MV will remain in the [0,1] interval. If x is close to b, the MV will be close to 1. If x is close to c, the MV will be close to 0. [24-26]

$$DOM\ (b) = max\left[min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right] \qquad (2)$$

2.2 De-Fuzzyfication output processing for membership allocations

At present, when Defuzzifying fuzzy data, the method that is selected most frequently is the Center of Gravity method. This method locates a centroid based on the fuzzy members that are outputted through the respective Outputs MF's. Essentially, the CoG method's main objective is to determine an x-coordinate such that if a vertical line was drawn through it, it would divide the shape of the fuzzy output into two halves that are equal mass (i.e., they would both contain the same total amount of "mass"). An equation (eq. (3)) below presents an example using the combination of the TMF and the TRMF to improve the performance of this study's proposed model [27-29].

$$CoG\ (c) = \frac{\int R * \mu(R)\, dR}{\int \mu(R)\, dR} \qquad (3)$$

2.3 Rules execution with fuzzy rule viewer for output processing for membership allocations

A fuzzy inference system employs the classic "IF-THEN" format to create a collection of cognitive-driven linguistic rules. The subsequent formula (4) illustrates the mapping of the implication on the x-y plane.

$$\beta_{0\rightarrow 1}\,(p, q) = \ [\beta_0\,(p), \beta_1(q)\,] \quad \text{Where}, \forall_p \in P \ \text{ and } \ \forall_q \in Q \qquad (4)$$

The following equation (5) was used to create fuzzy rules for the suggested research technique.

$$\beta_R\,(m, n) = \max\ [\min(\beta_m\,(m)\,, \beta_n(n)\,]\,, \min[(1 - \beta_M(m)), 1] \qquad (5)$$

The suggested study approach includes important elements for power transformer asset management. Figures (2) and (3) illustrate the cognitive rules for fuzzy inference. Rule viewer for Gouda is shown in Fig.2, IEC based method is shown in Fig.3 as output result of proposed fuzzy system respectively.

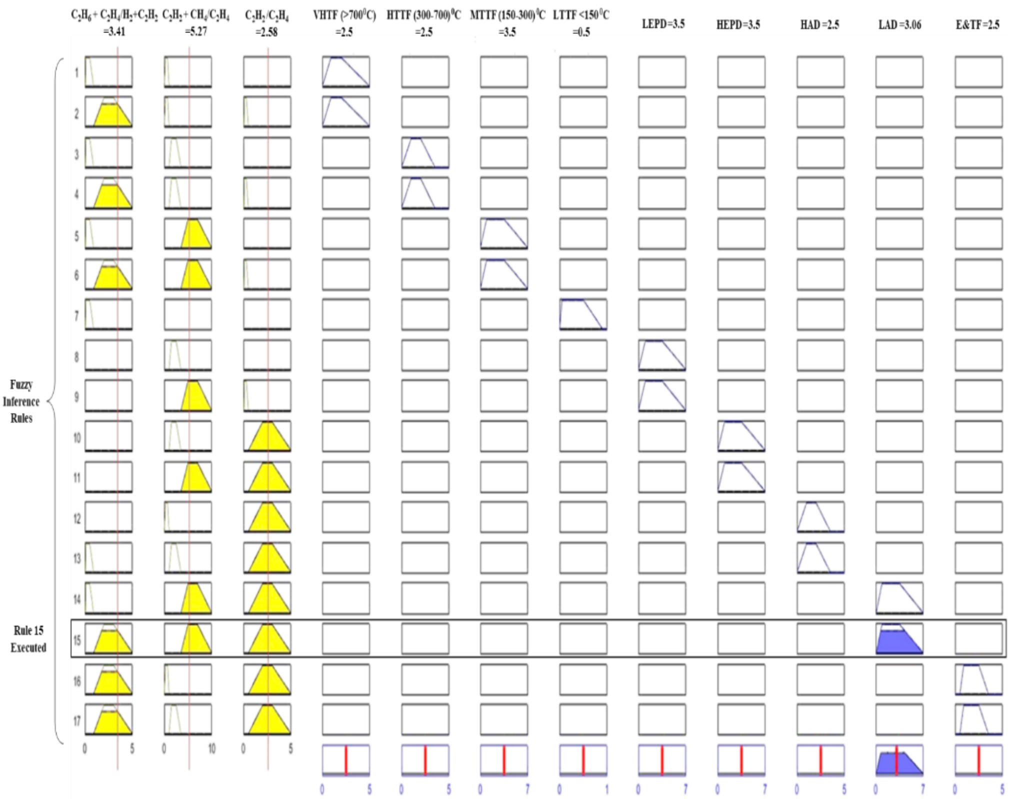

Fig. 2. Gouda's three ratio technique analysis with FLC in AI based modeling

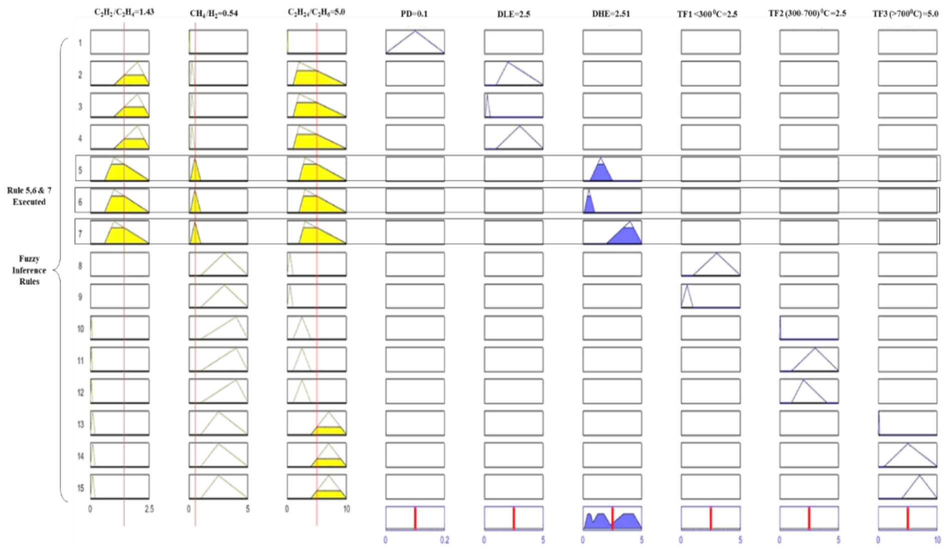

Fig. 3. IEC's gas ratio technique analysis with FLC in AI based modeling

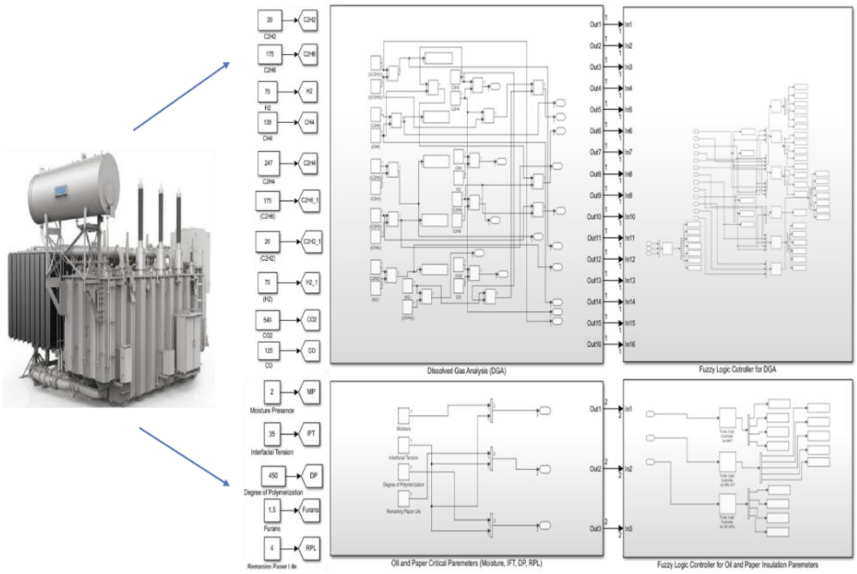

Fig. 4. AI based Simulink analysis for condition assessment of smart city power transformer

The FLC based simulation is utilized for two hundred data sets with MATLAB simulink model is depicted in Fig.4. However, Fig.5 shows 20 data sets out of 200 that contain essential characteristics employed in this work.

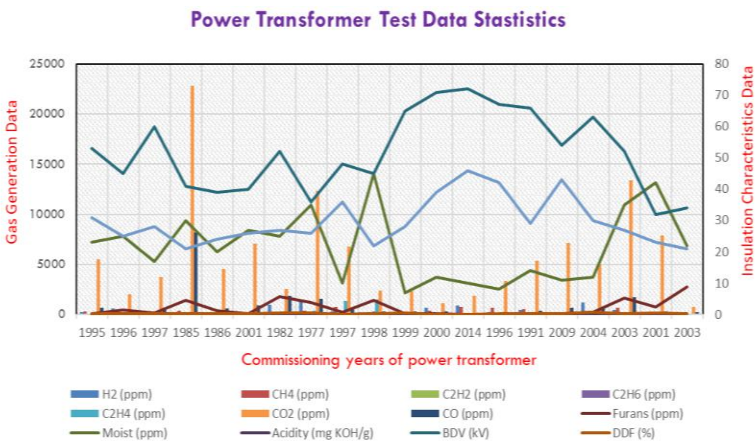

Fig. 5. Critical data driven analysis smart city power transformer

3 Result and Discussion

In this research power transformer asset management is shown with the use of fuzzy optimization. It is evident from the graphical abstract that a considerable accurate diagnosis, such as discharge of thermal faults can be made with the use of cognitive rules. Although there is a probability of many faults as shown in Fig.6 such as severe deformation or excessive aging, as an integral studies of winding deformations.

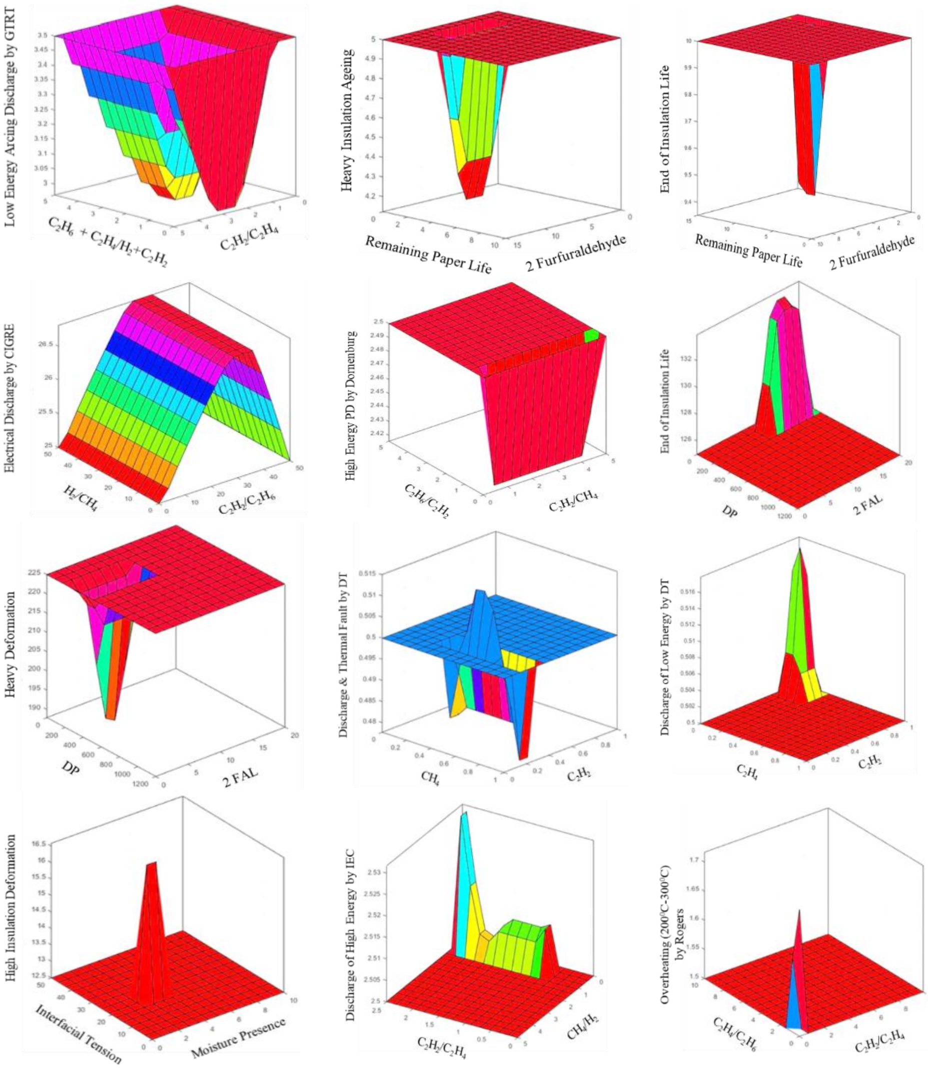

Fig. 6. Surface Analysis of Diagnosed Incipient Faults with Computational Intelligence

Further confusion matrix and ROC curve analysis are included for detailed analysis of transformer condition monitoring and its data driven approach in Fig. 7 and Fig.8 respectively.

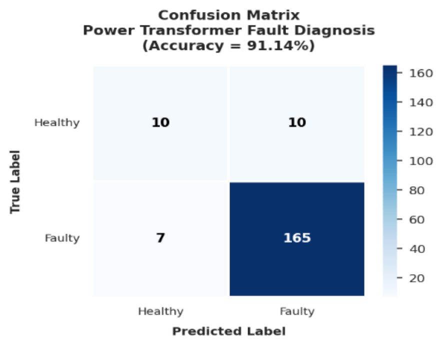

Fig. 7. Confusion matrix analysis for data driven transformer condition monitoring

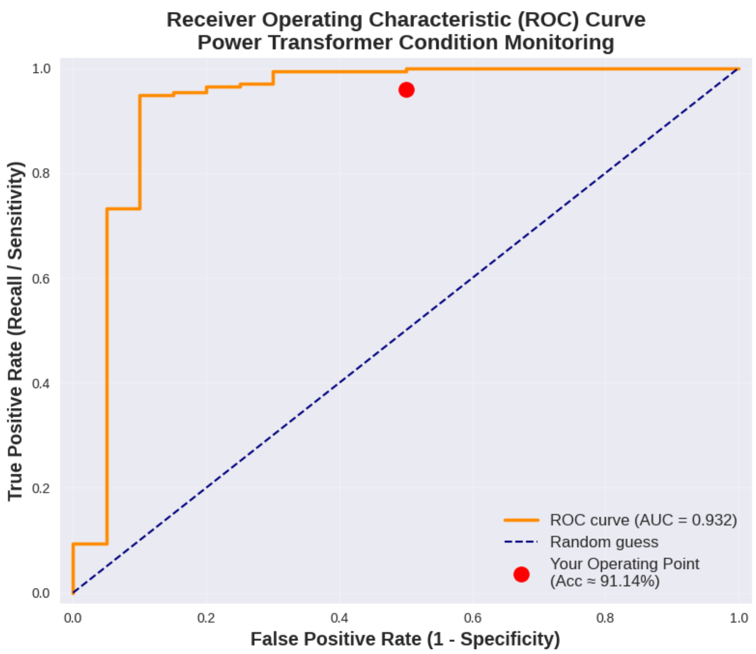

Fig. 8. ROC curve for performance analysis of power transformer condition monitoring

4 Conclusion and Future Scopes

This study has produced one fuzzy logic control (FLC) model and one decision support expert model based on the results obtained from 200 transformers. A comparison of the results achieved by the different methodologies tested showed that a method developed by Gouda, referred to as the three ratios method (GTRT), provides the best results with a performance of 97.5% highest, followed closely by those developed using furans diagnostic, moisture diagnostic and interfacial tension (IFT) diagnostic methods, respectively. A variety of conventional DGA methods are also employed, including IEC, Dornenburg, DP, furans, and others. When compared to previously published analytical, experimental approaches, this novel approach performs effectively and consistently because fuzzy logic has the cognitive power to rigorously analyze every alternative in order to discover the nascent deficiencies. Additionally, confusion matrix analysis and ROC analysis is also included to further enhance and analyze the data driven performance analysis of proposed model. More power transformer components and a thorough investigation of them can be done in the future. Furthermore, the analysis can be improved by sensor-based technologies along with more advance ML algorithms to overall enhance the efficiency of data driven condition monitoring model in smart city infrastructure.

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