Health Monitoring System for Generators Using AI Techniques

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***Abstract*—The development of a health monitoring system for electrical generators using AI techniques is presented. It focuses on Integrating AI techniques with Fuzzy based monitoring system for Generators health monitoring. Two AI systems such as ANN and FLS are simulated and tested to evaluate the performance monitoring for generators. A comparison between the two AI methods are done. Fuzzy Logic System was found to have a higher efficiency over ANN. For the possible causes of the fault, ANN and FLS have produced 70% and 100% efficient respectively.**

Keywords— ***Generator health monitoring, ANN-based monitoring, Partial discharge, generator temperature, fuzzy logic.***

I. Introduction

The power system is a combination of a network consisting of generation, distribution, and transmission systems. It uses forms of energy like coal, fuel, etc to produce electrical energy. The main components of a generating station are the generators and the transformers. In generating stations fuels (water, nuclear energy, coal, etc.) are used for converting mechanical energy into electrical energy. The mechanical energy produced comes from the burning of fuels like coal, gas and nuclear fuel, gas turbines, etc. The electrical power generated in the generating stations is around the range of 11kV - 25kV, which is then step-up for long-distance transmission. Since the generator is the source of the production of electricity, monitoring its working condition is vital [1].

Improper maintenance will lead to generator failure, which will cause failure in the production of power, thus resulting in unwanted downtime [2]. The expectancy of the generator is critically reduced if it's overloaded, resulting in unexpected failure, thus affecting its reliability [3]. Generators will have a long service life if it is accurately monitored and operated under well-maintained conditions. The system has presented to monitor the generator characteristics of a steel melting shop, which will be notifying the end-user through GSM service i.e. text messages. The system will be notifying critical generator problems to the user, to ensure timely diagnosis and minimize downtime [4]. Another study has presented the online condition monitoring of a large synchronous generator under a short circuit fault. It is of utmost importance to diagnose the defects at an early stage. The process of fault diagnosis involves the detection of the type of fault and its severity [5]. The realization of a low-cost wind turbine emulator has designed for conditioning monitoring and diagnosis [6]. An economical phase power quality disturbance generator for generating voltage sag and swell for short and long interruptions are analyzed and designed a real-time monitoring system to evaluate the performance of the generator through voltage swag, swell, harmonics, and interruption [7]. The researchers proposed a monitoring system for pellets mill power transmission, which uses AI techniques for analysis. The parameter measured for the condition monitoring is the vibration of the machine which is the main cause for major damages [8].

The researcher attempted to review and summarize the research in the field of signal analysis by using Artificial Intelligence, for fault diagnosis and condition monitoring. Different methods for condition monitoring have been tested [9]. It has developed a control monitoring system of machine parameters for a processing company. The monitoring is done through the AI technique of Fuzzy logic [10].

The generator model was constructed with a memory matrix, of the generator dataset. ANN was implemented to determine the condition of a generator, by understanding the trends of deviation of parameters values in working and faulty cases [11]. The researchers have identified the generator factors such as ball-bearing defects, rotor imbalance, and electric load imbalance. The detection of the parameters was performed through the wavelet power spectrum analysis of vibration signals. Three tests were done, namely, short-time Fourier transform, continuous wavelet transform, and order analysis. Common faults were simulated for a test facility of 500W permanent magnet motor, signal analysis, and the diagnosis of fault was done under constant and variable speed.

The gearbox monitoring system for different fault and operating conditions are developed using the AI technique. There are three AI techniques used in the system, namely, General Regression Neural Network (GRNN), Back Propagation Neural Network (BPNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) to capture variations in motor current and parameters like temperature and load settings [12].

A time-based condition monitoring system using Neural Network and Fuzzy Logic is developed to monitor the health of generators. The AI systems were applied to predict the fault types of the mechanical system. The accuracy of both the AI systems were discussed and concluded that Fuzzy Logic is less efficient compared to AI techniques [13].

Generators are the primary source of energy conversion in all categories of power generation plants, as a main source of energy in an electrical network, it is of vital importance that the generator health is maintained to avoid unnecessary and costly downtime. Managing a power plant in today's competitive and high demand industry means controlling the risk of failures with dire consequences. Monitoring the generator characteristics is crucial, factors like vibration, coolant temperature, generated power, generator runtime, winding conditions etc, affect the efficiency and the production capacity. The breakdowns and malfunctions will also produce an adverse effect on the production line. Hence a constant need for monitoring and power supply is needed.

Artificial Intelligence-based monitoring system will help in tackling major problems on generator monitoring and maintaining its longevity. The appropriate system is essential to notify on detection of abnormal generator behavior and reporting critical problems, which will minimize downtime and maximize availability. AI-based monitoring system will offer instant diagnosis, which can help cut down on operational costs and improve the lifetime of generators.

This work emphasizes the integration of Artificial intelligence to the generator monitoring system to ensure the maintenance needs are met to accuracy and to reduce its dependence on the plant operators and workers, thus making it free from human errors. A smart Artificial Intelligence-based generator monitoring system will be developed. The monitoring system will be keeping in check the generator parameters like output power, conditional monitoring, oil level, etc. The system has developed using Artificial Intelligence techniques integrated with the monitoring system. AI helps to predict the accurate generator measurements and proper generator analysis.

II. BLOCK DIAGRAM AND OPERATION OF THE PROPOSED SYSTEM

A. General Block Diagram

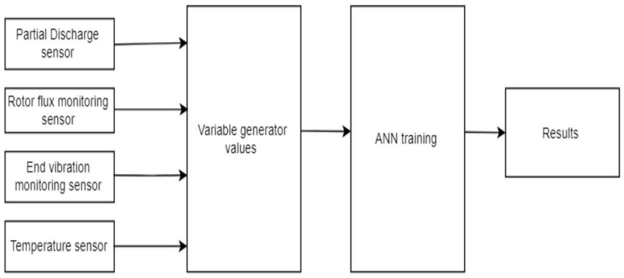

Fig. 1. General block diagram

The block diagram of the overall framework of the system is demonstrated as shown in Figure 1. It is in four parts, sensor readings, variable value generator, AI trained block, and simulation results. The monitoring parameters, partial discharge, rotor flux monitoring, end vibration, and temperature are all having their specific values, each of which is obtained by their respective sensors. To simulate a real-time generator like condition, a system will be made which automatically generate the readings of all the available monitoring data. With the help of MATLAB's Artificial Intelligence toolbox, the Artificial Neural Network technique will be developed for monitoring. The AI system checks through the data and offers corresponding results. The results are shown in charts, plots, and LED signals, depending on the monitoring parameter.

The condition monitoring of the generator requires proper identification of the parameters. Long term running causes the in-turn rotor to bend, thus increasing unbalanced magnetic pull, leading to vibrations. The increase in vibrations causes an increase in Partial discharge, resulting in insulation system problems, which leads to an increase in short circuit fault. The inter-turn short circuit of the rotor winding causes the magnetic field to go asymmetrical. The distortion causes the current to pass through the rotor shaft. The air gap monitoring between rotor and stator will help to detect the loose movements and misalignments. The monitoring of generator temperature in line with operating conditions would help in detecting the fault in the cooling systems.

B. System Block Diagram:

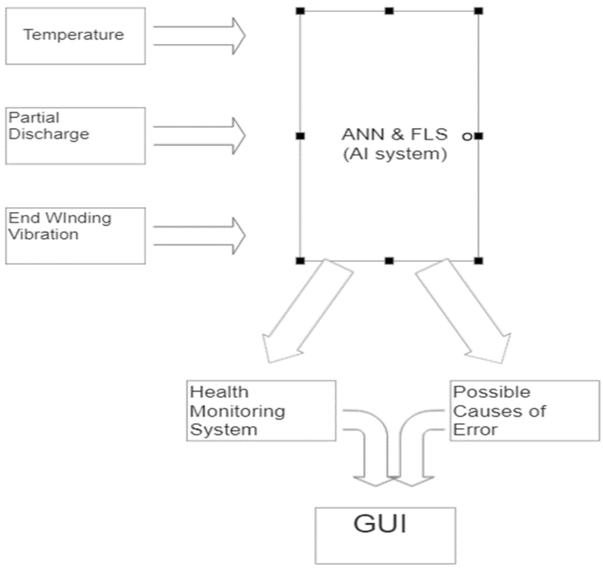

Fig. 2. System block diagram

Fig. 2 shows the complete system block diagram. It starts with the input of the three generator parameters, which are temperature, partial discharge, and end winding vibration. The input parameters are fed into the AI systems. Two AI systems such as ANN and FLS are created and acquired the generated outputs two cases for monitoring the parameters and identify the possible causes of the fault. The output generated is then displayed using the GUI for continuous monitoring. The system notifies if the generator is under working conditions, or critical and faulty condition. Moreover, the system gives information on the possible causes of the fault. It refers to the critical values of the parameters and suggests what type of fault might have occurred. The 20 KV generator called Hydro generator connected with gas-cooled has implemented to monitor the critical values of the parameters. As can be seen from the system block, insulation damage occurs the most out of all other cases. Partial Discharge is both, a major cause and an indicator of deficiencies in stator winding insulation. Therefore it is effective in identifying Insulation defects and faults. The PD is the most effective dielectric measurement for early detection of failures and has been implemented with significant achievement.

Generator stator windings outside of the stator core are referred to as the end-winding. The end winding operates at high-voltage and needs assistance against mechanical vibration powered by mechanical and magnetic forces. End windings of the machine are intended to control these vibrations sufficiently in ordinary conditions to avoid important motion Faults happen when the bracing structure slackens at the end of the winding, either due to a sequence of uncommon overloads or due to a prolonged ongoing operating period. The end winding insulation gets broken or worn away in some instances.

The measurement for vibration is determined by its periodic movement of back and forth, which is its peak to peak displacement, denoted as "µm p-p". Peak to peak is the amplitude from time waveform positive peak to negative peak. The standard monitoring levels for end winding vibration monitoring, based on a large synchronous generator working at 60 Hz, have an acceptable range of radial displacement magnitudes between 50-125 µm peak to peak.

C. Artificial Neural Networks (ANN) training

The training for ANN was done on MATLAB Neural Network toolbox. Various training types according to the problems to be solved, were provided by the toolbox namely, Input-Output curve fitting, Pattern recognition-classification, and Dynamic time series. Fitting type network maps between a data set of numeric inputs and a set of numeric outputs, fitting problems generally include systems used for monitoring and prediction. The monitoring system in the project falls underfitting. The network type chosen for the training is "Feed Forward Back Propagation Neural Network (BPNN)". BPNN works in two steps, the first step is to feedforward, where, neural network information flows from the input layer to the output layer, and weights are decided. BPNN was chosen due to the differences in the output efficiency. BPNN takes more time to train the system but has higher efficiency and produces fewer errors when compared to the GRNN outputs.

To train the Neural Network, dummy data sets were created from the faulty parameter values obtained from journals and research papers. The values of the temperature and partial discharge are measured using two digital sensors. The operating voltage of both sensors are sharing 5V of power supply and common ground from the Arduino MEGA - ATmega2560 through the breadboard.

D. Fuzzy Logic Training

Fuzzy Logic (FL) is a technique similar to human reasoning. FL imitates the manner of human decision making. It includes all intermediate-range of possibilities between YES and NO, such as " CERTAINLY YES", "CANNOT SAY", "POSSIBLY NO" etc. Hence, the fuzzy logic operates to obtain the definite output on the level of input opportunities. The training for the Fuzzy Logic System (FLS) was done on MATLAB Fuzzy Logic Toolbox. Fuzzy Logic's architecture contains four parts :

- Rule Base: It operates on the guidelines of IF-THEN condition requirements provided by the specialists for decision making based on Linguistic information. Linguistic variables are input and output variables in the form of simple words or sentences. For the monitoring system's parameters, there are linguistic terms, each.

Inputs

Temperature = {Low, Normal, Critical}

PD = {Low, Normal, Critical}

EWV = {Low, Normal, Critical}

RTM = {Low, Normal}

Outputs

Alert = = {Low, Normal, Critical}

Winding Insulation Damage= {Low, HIGH}

Overload = {Low, HIGH}

Loose Stator Windings = {Low, HIGH}

Rotor Imbalance = {Low, HIGH}

Shaft Misalignment = {Low, HIGH}

End Winding Insufficient Spacing = {Low, HIGH}

- Construct Membership Functions (MF): It is a graph that defines how to map each point in the input space to the membership values between a set of numbers. Input space is often referred to as the universal set (u), containing all the relevant elements of concern, as described in "Rule Base

Two types of membership functions have been used for system development. The first one is triangular membership function, which is defined by a lower limit of "a" and an upper limit of "b", and a value "m" such that, a<m<b. The second one is the SMF and ZMF membership function. The MF for "Low" is ZMF, which is the Z-shaped MF, and the MF for "High" is SMF, which is the S-shaped MF.

III. PERFORMANCE TESTING AND SIMULATION RESULTS

The overall performance of the developed system has evaluated by conducting various simulations using AI and neural network platforms.

A. Simulation of monitoring system using ANN

The training of ANN for this test was done on the "Neural Network Toolbox" for MATLAB. The monitoring system has notified the user if the condition of the generator is under working condition or critical. The three parameters, Temperature, Partial Discharge, and End Winding Vibration are tested with various inputs to test the monitoring ability of the system developed. The Neural Network trained was made into a Simulink block for the ease of testing. The first testing will be done for Temperature ANN block, where values for the three conditions, Low, Working and Critical will be given as an input and its output will be noted. The experiment will be then followed by PD and EWV. The outputs are represented in the binary codes as Low = 1000, Working = 1010, and Critical = 1110.

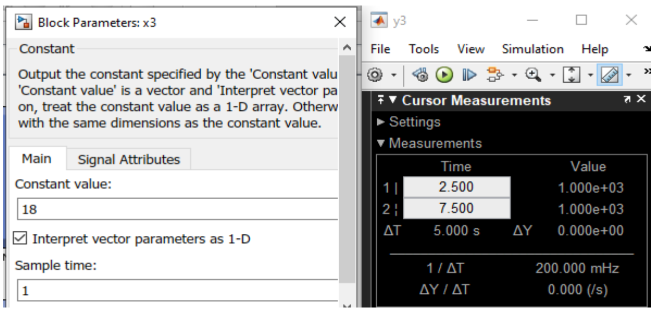

Fig. 3. Temperature Block

The temperature block is shown in Fig. 3 and the parameter values for monitoring conditions for temperature are as follows, Low = <40 °C, Working condition= 40-140°C, and critical condition =>140°C. The inputs and outputs are done through ANN Simulink block, where a constant input value is provided, and the output generated by the Neural Network system is generated. prediction boundary.

The partial discharge values for the monitoring conditions for PD, are as follows, Low = <18 mV, Working condition= 19-60mV and critical condition =>60mV. The inputs and outputs are simulated through ANN Simulink block, where a constant input value is provided, and the output generated by the Neural Network system is generated, which are shown in the Fig. 4.

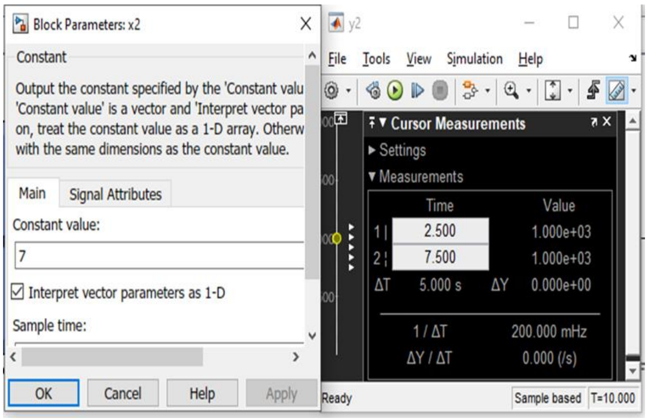

Fig. 4. Partial Discharge Detection

B. Monitoring system using FLS

The training of the system using FLS was very different than ANN. FLS was trained to create a relation between inputs and outputs and then defining the rules. The input parameter values, Temperature, PD, and EWV were divided into 3 parts each, using 3 MFs, which were titled as Low, Normal, and High. One extra input for Fuzzy logic is the Running Time (RTM), which has a value of High and Low.

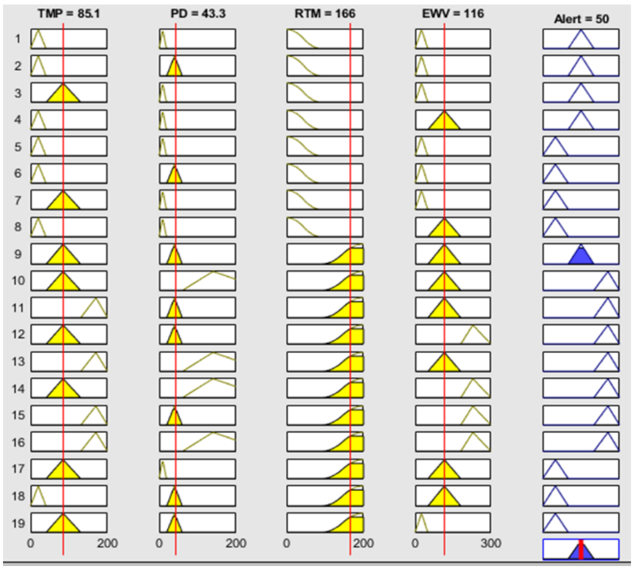

Fig. 5. Fuzzy Temperature Alert-Low working

For testing the generator health, the input values of the parameters have been kept same as the ones used for testing the ANN system. The output generated here is based on the rules defined. The whole fuzzy system is created under one user Interface block, unlike ANN where the blocks of the monitoring system and the possible causes of fault were made separately. However, the testing for each parameter has shown separately.

Fig. 5 shows the condition where the temperature is 25°C, which is lower than the normal working condition, PD is 43.3 mV and EWV is 116 Qm, both of which are in the range of their normal working condition's values. RTM is kept to a high value, which means the generator is not under the starting stage. Hence the value under Alert is "16.7" which is in the range of Alert's "Low" membership function's value. Thus, the output generated says, the system is under "Low working condition".

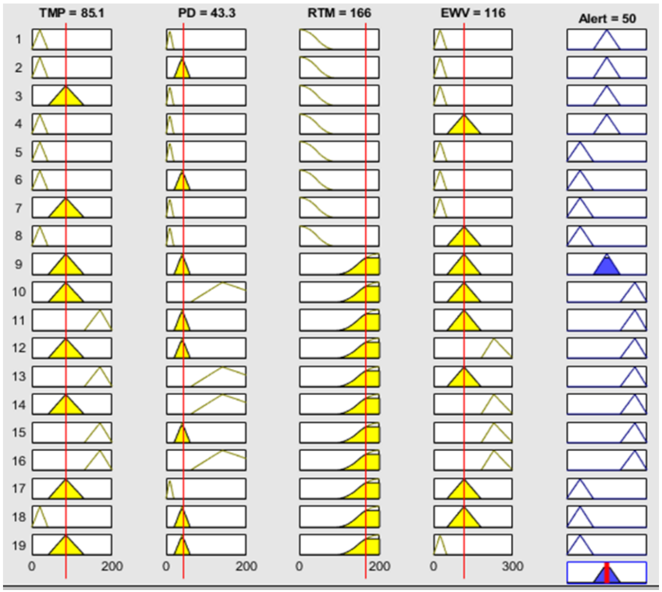

Fig. 6. Fuzzy Temperature Alert-Normal working

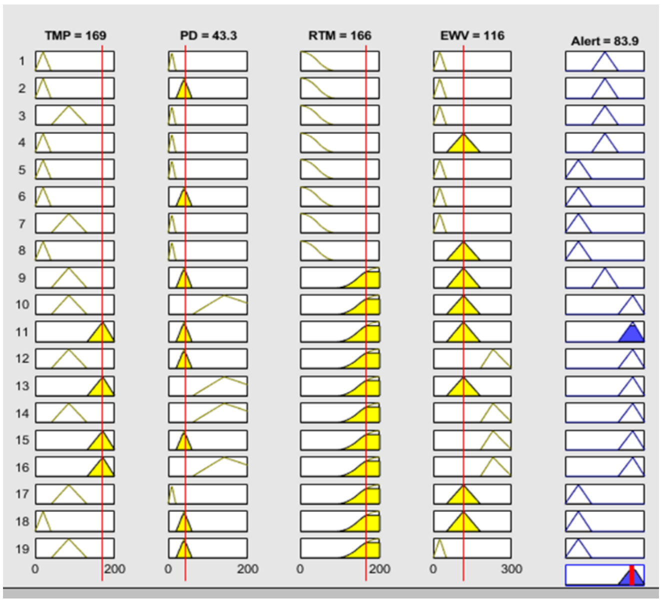

Fig. 7. Fuzzy Temperature Alert-Critical working

Fig. 6 shows the condition where the temperature is 85.1°C, which is in the range of Normal working conditions, the PD, and EWV, both of which are in the range of their normal working condition's values. RTM is kept to a high value, which means the generator is past its initial starting time not under the starting stage. Hence the value under Alert is "50" which is in the range of Alert's "Normal" membership function's value. Thus, the output generated says, the system is under "Normal working condition".

The Fig. 7 shows the condition where the temperature is 169°C, which is in the range of its Critical working condition, the PD and EWV remain unchanged, both of which are in the range of their normal working condition's values. RTM is kept to a High. The generated value under Alert is "83.9" which is in the range of Alert's "Critical" membership function's value. Thus, the output generated says, the system is under "Critical working condition".

Similarly, to the Temperature testing, Fig. 8 shows the testing for PD. The PD value given as an input to the fuzzy system is 10.4 mV, which is lower than the normal working condition's value. The value for Temperature and EWV is under normal working condition RTM is kept to a High. The generated value under Alert is "16.7" which is in the range of Alert's "Low" membership function's value. Thus, the output generated says, the system is under "Low working condition". Subsequently, the Fuzzy based monitoring has performed for Normal and Critical conditions respectively.

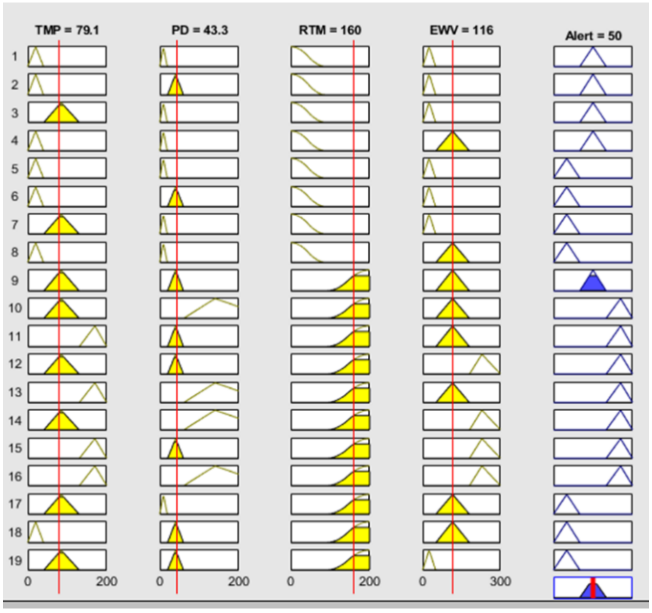

Fig. 8. Fuzzy PD Alert-Low working

Similarly, to the previous two testing done for Temperature and PD monitoring, Fig. 9 shows the testing performed for the parameter EWV. The temperature and PD parameters are kept in Normal working conditions, and RTM is kept high to conduct this monitoring. Subsequently, the same testing has been done where two parameters are kept to critical, normal, or working conditions, to show that the system gives the accurate monitoring output, even when multiple inputs are provided. Subsequently, the Fuzzy based monitoring has performed for Normal and Critical conditions respectively.

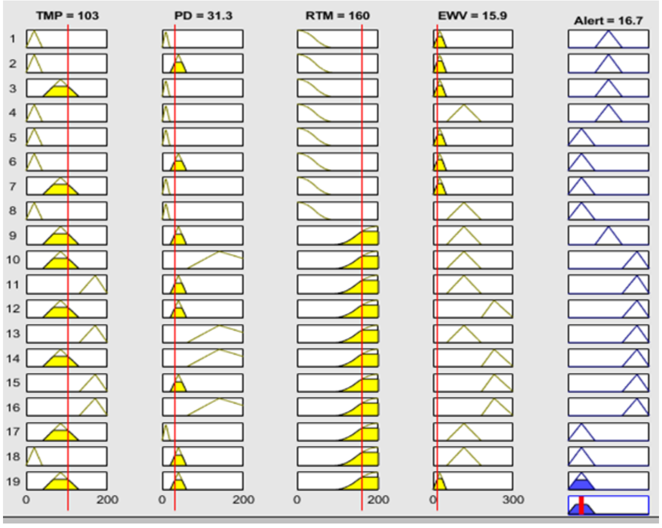

Fig. 9. Fuzzy based EMV testing

C. *Performance Evaluation*

The performance evaluation between both the AI systems are carried out to find out which one has a higher efficiency. The input values given to both the AI systems will be the same, and then the generated output will be compared. The input parameters are in the order of Temperature, PD, and EWV. The values are tabulated in Table I.

Table I. Monitoring system performance evaluation

Input	ANN outputs	FLS outputs
82,40,116	1010	50
112,25.4,148	1110	50
16.4,37.3,16.7	1000	16.7
79.1,166,120	1110	83.8
160,166,225	1110	83.8
172,37.3,216	1110	83.7
58.2,31,3,139	1110	83.6
22.4,10.3,22.3	1000	16.7
Error	0%	0%

From both the cases, it can be concluded that FLS has a higher efficiency than ANN. For the possible causes of the fault, ANN was 70% efficient, whereas, FLS was 100% efficient. Hence, FLS would be a better choice over ANN for the proposed system.

IV. Conclusion

The development of a health monitoring system for electrical generators using AI techniques is demonstrated. There are two types of AI methods, ANN and FLS are used and developed the simulation-based health monitoring platform. The AI system was divided into 2 parts such as health monitoring and fault display system respectively. It is observed from the first system is that both ANN and FLS can produce 100% efficiency in the monitoring purpose. It could be identified using conditional parameters of Low, Normal, and Critical conditions. Further, the fault detections are observed using the second system. It also observed the parameter variations and compared the results of FLS and ANN. The simulated efficiency for fault detection of ANN and FLS is 70% and 100% respectively.

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