Use of Adaptive Neuro Fuzzy Inference System for Fault Diagnosis of Power Plant

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Abstract: **This work used the ANFIS (Adaptive Neuro-Fuzzy Inference System) as a framework to diagnose faults in the boiler section of a power plant. A backpropagation algorithm was used in modeling the ANFIS network. Industrial boiler data were obtained from the power plant, compiled using Excel, andthe ANFIS network was then simulated using Artificial Neural Network Tool in MATLAB2015a. A GUI (Graphical User Interface) was generated to easily interpret the fault results obtained. After the simulation, the ANFIS network was tested using the industrial data and using the Graphical User Interface, it was able to identify the size, root causes, and location of the faults and gave an explanation as to the corrective measures required for all the five faults that occurred in the power plant to be remedied. When the boiler was operating at its set point/standard value no fault was observed. Boiler overheating was experienced when the temperature of overheated steam and super-heated steam pressure increased from their points. Boiler feed pump failure occurred when there was a deviation from the setpoint value of the feedwater flowrate. The boiler plant used was that ofthe Egbin power plant in Lagos.**

Keywords: **ANFIS, boiler plant,setpoint, explanation ability, graphical user interface, root cause.**

I. INTRODUCTION

A Fault is generally defined as the departure of an observed variable or calculated parameter from an accepted range (Barak, 2016). The monitoring of industrial processes for performance and fault detection is an essential part of the drive to improve process quality. The requirements of improved productivity, efficiency, safety, and reduced levels of manning have led to the increased investigation into fault detection and diagnosis. With the increased use of instrumentation, huge quantities of dynamic plant data are available in real-time. Regulatory control actions are now routinely performed by computer systems with considerable success. The role of operators and control systems hasshifted from being primarily focused on regulatory control to a broader supervisory role. The data available from a plant contain hidden redundancies together with important information about impending and current faults, as well as process performance. Unfortunately, much of this information is not used due to the problem of the complexity of extracting the complex relationships from within the data. Human reactions still serve as the primary response to detecting and diagnosing faults in chemical processes. Consequently, considerable valuable knowledge is not utilized to identify, prevent, and respond to faults and other undesirable operating conditions in the plant (Fourier (2017)). Multivariable statistical approaches to process monitoring, fault detection, and diagnosis are well accepted and rapidly developing. The techniques have the ability to extract useful relationships from massive data sets. These relationships can be monitored for faults and analyzed to aid diagnosis of these faults (Ahmad et al., 2017)

ANFIS is a modeling algorithm with diverse applications. Esfahanipour and Aghamiri (2017); Chang et al. (2016). Saleh and Hussain, (2016) applythe ANFIS model for stock market predictions and stock price index analysis.In another study conducted by Chen (2019), the ANFIS model was used for predicting business failure prediction using particle swarm optimization and subtractive clustering.In the field of telecommunications, Chen H et al. (2018) developed a robust prediction model using ANFIS based on Terrestrial Trunked Radio (TETRA) outdoor Radio Frequency (RF) measurements. This model was used to predict the strength of the wireless signal received by wireless devices. In another study ANFIS was used, in addition to a Finite Element Model (FEM), to predict the wafer surface non-uniformity in a chemical mechanical polishing (CMP) process. The data ANFIS trainedwas obtained under several conditions of the carrier load, elastic modulus, and thickness by using the developed finite element model for CMP.M process, Ahmed and Shah. (2017).Naghibzadeh (2018) applied ANFIS for the fault diagnosis of the polypropylene production process (UNIPOL PP). The study was on fast and accurate diagnosis, multiple fault identification, and adaptability. Simulation results showed that the method effectively diagnosed different fault types and severities. It was also observed that it had a better performance compared to a conventional multivariable statistical approach based on principal component analysis (PCA). ANFIS is robust to measurement noise, and it was able to rapidly discriminate between multiple faults occurring simultaneously.

Vivekanandan et al. (2017) applied ANFIS for modeling an anaerobic hybrid reactor (AHR). The hybrid reactor was used in treating penicillin – G wastewater at the ambient temperatures of 30 – 35 °C for 245 days in three phases. It was concluded that the ANFIS model was well performed in predicting the performance of the AHR (Vivekanandan et al., 2017). Beheshti, et al., (2016), Moghadam, et al (2019), Azimi et a (2018) and Jasbi et al (2018) applied ANFIS in rainfall forecasting, prediction of hydraulic jump length on slopping rough beds and predicting roller length and agility in supply chain respectively. These show the divers modeling and computing that ANFIS has been used recently.

II. MATERIALS AND METHODS

2.1 Study area and industrial boiler data

Egbin steam generator is a fire-tube boiler with radiant natural circulation with single reheat duct firing. The steam generator has the capacity of producing 705metric tons/hr. of steam. The boiler feed pump{BFP} supplies the drum with treated water from the water treatment plant at the flow rate of 62750kg/hr.The furnace provides the platform through which the fuel oil/natural gas undergoes combustion in the presence of preheated air and an ignition source, to produce combustion products or flue gases.Flue gases or combustion product passes through the furnace chamber transferring heat to the radiant tubes containing natural circulating water, superheated reheater, economizer, air- preheater, gas collector and then ejected through the stack.The superheated steam under controlled temperature is piped to the high-pressure turbine to turn the rotor, and by this action, the temperature and the pressure of the steam leaving the high-pressure turbine to reduce to 351C and 69 0kPa respectively. This steam is then channeled back to the preheater which increases the temperature and pressure to about 541C and 3130kPa, and then channel to intermediate pressure turbine to also turn the rotor and finally to the low-pressure turbine where it also performs the same function.The steam leaving the low-pressure turbine is condensed and with the aid of the condensate extraction pump returned to the boiler drum completing the continuous process of the water–steam path.

2.2 Major Component of Egbin Steam Generator:

The steam generators,a major function is to produce steam and it consists of the following units:

- The boiler: this consists of the drum, downcomer, water wall, safety valve, vents, drain, blowdown, flash tank, etc.
- The furnace consists of the burner, refractory, insulation, and casing. The furnace chambers contain the following devices installed strategically for effective heat regeneration Superheater, Reheater, Economizer, Air preheater.

2.3 Data preparation

Data for analysis were collected from the power plant at Egbin in Lagos. The dataset was divided into boiler input and output and saved in excel files because the data were so large.The boiler input and output dataset were then imported individually into MATLAB command using the "import data" in the MATLAB command window. The command nntool was typed in the MATLAB command area to display the neural network dialogue box.In the import section of the neural network dialogue box., boiler input and output data were imported by selecting appropriate buttons and then clicking the import button. The "New Button" was clicked to display the create network dialogue box, it was named "ANFIS network", the network type was selected "Feed-Forward Backpropagation", performance function was selected "Mean Square Error", the number of layers and neuron to be used was selected and the "Create button" was clicked to create the network.The Train button was clicked and the max_fail value was inputted as 1000 in the training parameter section in order for the validation check of the data to be trained 1000 times, epoch value was 1000, and the regression, training state, and performance plot of the trained data was generated. The created ANFIS network was imported for use in the Matlab workspace using the "import button".

2.4 Adaptive neuro-fuzzy inference system (ANFIS)

The architecture of ANFIS consists of five layers. There are two types of fuzzy rules the Takagi – Sugeno and the Mandani fuzzy rules. In this work, Sugeno rules wereused.The hybrid learning algorithm allows identifying parameters of the Sugeno type fuzzy inference systems. This method applies the combination of the least square method and the backpropagation gradient descent method for training FIS membership function parameters.

2.5 Description of the system

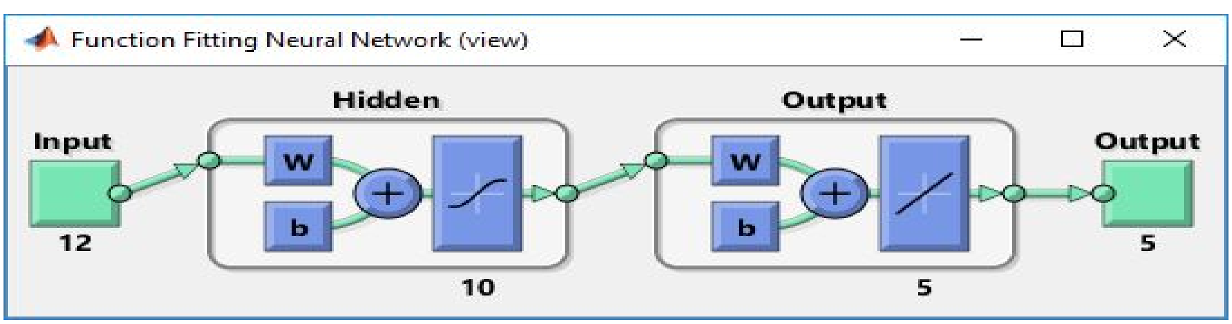

Fig 2.1 ANFIS for Twelve Input Sugeno Fuzzy Model

The five-layer identified in the figure are fuzzy layer, product layer, normalized layer, de- fuzzy layer, and output layer.The first order Sugeno fuzzy model is a linear model, which allows the use of the consequent part (i.e. the THEN part) of the fuzzy inference system having linear values, and the parameter is predicted by the least-squares error method.Let the fuzzy have two inputs, x and y, and one output z. Then, there would be two rules as follows:

Rule 1 IF X is A_1 AND Y is B_1 THEN $Z_1 = p_1x + q_1y + r_1$ (1)

Rule 2 IF X is A_2 AND Y is B_2 THEN $Z_2 = p_2x + q_2y + r_2$ (2)

A_1, A_2, AND B_1, B_2 are membership functions for the inputs X and Y respectively.p_1, q_1, r_1, and p_2, q_2, r_2 are constants to be determined using the least square regression method. The values of the constants are in the then part of the rule. They are known as consequent parameters.Layer 1 the input nodes are adaptive nodes that generate membership values of the linguistic variable. Here v and d are input to the system. $0_{1,i}$ is the output of the 1st node of layer 1. These adaptive nodes are squares with square – function. This square function is defined by equation 2.

$0_{1i} = \mu v, i(v) \text{for} i = 1,2$ (3)

$0_{1j} = \mu v, j(v) \text{for} j = 1,2$

0_{1i}and0_{1j} denote output function and $\mu v, i$ and $\mu v, j$ denote membership function. The computation of the membership function can be done using Gaussian membership (parameters here called premise parameters (i.e., the if – rule part).Layer 2 here, every node is fixed. Its function is to receive input values v_1 from the first layer and act as a membership function in the respective input variable to check the weights of each membership function. It estimates the firing strength (w_1) of a rule. The equation describing it is.

$0_{2,i} = wi = u_{v,i}(v).\mu D, j(d), i = 1,2$ (4)

Layer 3. The node here is also a circle and is labeled N. The N there indicates that normalization of the firing strength from the previous layer. The output is $\overline{w}_1$ as shown in Eq. (5).

$0_{3,i} = \overline{w}_i = \frac{w_i}{w_i+w_2}, i = 1,2$ (5)

The output is known as normalized firing strengths.

Layer 4. The nodes in this layer are once more adaptive nodes. The output is a product of the normalized firing strength and first-order polynomial. The weighted output of rule is represented by node function in Eq.6

$0_{4,i} = \overline{w}ifi = \overline{w}_i(piv + qid + ri) \quad i = 1,2$ (6)

$0_{4,i}$ Denotes the output from layer 4. $pi, qi, ri$are the consequent parameter and f_i is a linear function of input variables.

Layer 5. This layer aggregates the consequents to produce a crisp output. The single node in this layer is fixed and it transforms fuzzy classification results into crisp (ordinary number) values. It computes the weighted average of all incoming signals to calculate output signals as shown in Eq.7

$0_{5,i} = \sum i\overline{w}ifi = \frac{\sum iwifi}{wi+w2} \quad i = 1,2$ (7)

Table 1Showing Boiler Measured and Unmeasured Nodes

Measured Node		
Nodes	Parameter/Units	Values
P_A	Feedwater pressure	13,979kPa
F_A	Feedwater flow rate	66,500kg/hr.
FC	Overheated steam flow rate	18,475kg/hr.
F_B	Cooling water flow rate	64,750kg/hr.
T_A	The temperature of the overheated steam	335 °C
P_C	Boiler drum pressure	13680kPa
P_B	Super steam pressure	12,990kPa
T_B	Hearth temperature	1,297°C
F_D	Flow rate of air	825,400kg/h
O_A	Oxygen percent in fuel gas	6.8%
F_E	The flow rate of fuel oil	548,310m^3/h
P_E	Pressure of hearth	1130kPa

Table 2.2 Showing Boiler Fault

	Boiler Faults
1	Boiler feed pump failure
2	BoilerOverheating
3	Burner capacity low
4	Low Boiler Blow-Down
5	High-Pressure Trip in Boiler

Generated MatlabGui For Fault Diagnosis

A Matlab GUI (Graphical User Interface) was created using Matlab where the trained ANFIS network was interfaced with the created GUI and tested for diagnosis of faults. The Matlab GUI was coded with the 12 input boiler data and 5 output boiler data. For easy interpretation, the following features were created;

*1.Monthly Maintenance:*This feature contains the routine maintenance required for the boiler which is to be carried out by the boiler operator or maintenance unit monthly in order to maintain efficiency and increase the useful life of the boiler.

*2.Analyze Fault:*This feature contains the root cause of the fault and the required actions to be taken for the fault diagnosis.

*3. Boiler Input Variable Column:*The 12 boiler input variable column was designed with numerical values and setpoints. These columns allowed the user to be able to input the data obtained from the boiler daily and diagnose the faults. This can also be interfaced with the equipment for online diagnosis

4. Anfis Train Data: This feature allows the user to train the desired data using the neural network tool in the Matlab environment.

5. Diagnose Fault: This feature contains the trained network which is used to diagnose the inputted data and displays the magnitude of the corresponding output data using the feed-forward backpropagation algorithm.

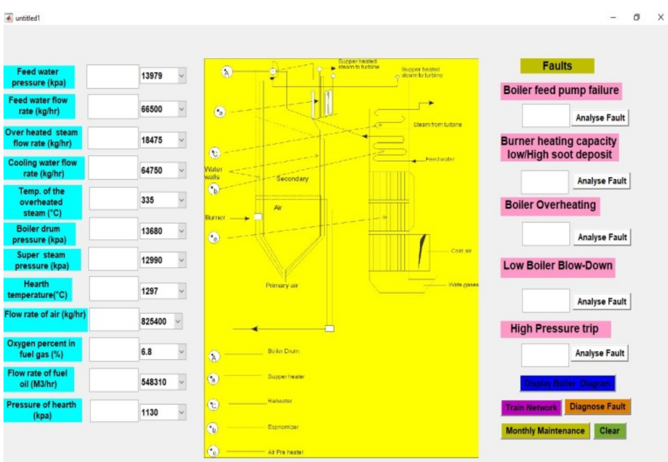

Figure 2.2 Generated Matlab GUI

III. RESULTS AND DISCUSSION

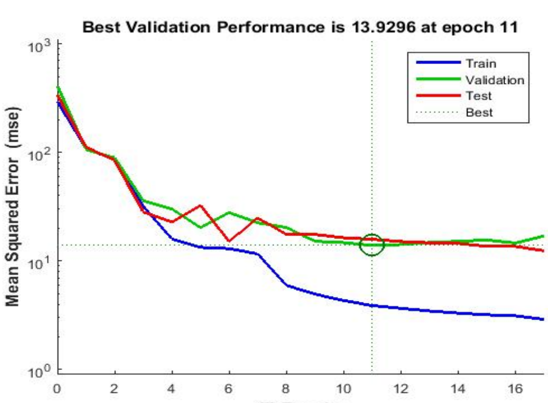

Figure 4.1 Best Validation Performance plot

The data from the plant was divided into three. Training data, validation data, and testing data. The best-validated performance plot was used to show the fitness between the train, validation, and test dataset of the boiler input and output data. This was done by calculating the mean square error(MSE) of the data obtained and plotting against the number of epoch trained by the network. After training the ANFIS network, the value for the best validation performance was calculated as 13.9296 at epoch 11.

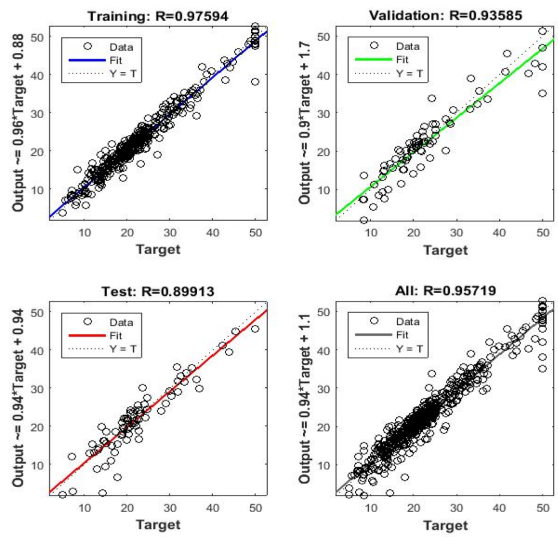

Fig4.2 Regression Plot

The Regression plots showed the fitness between the output data of the trained ANFIS network and the target value initially inputted before training by the ANFIS network. This was done for both the training, testing, and validation data. The more the fitness, the more accurate the trained ANFIS network is when used for fault diagnosis. The correlation coefficient (R) was found to be 0.97594, 0.89913, 0.93585 and the mean squared error(MSE) was found to be 3.17, 0.42,8.15 for training, testing and validation respectively

Evaluation of ANFIS performance

The faults size or magnitude was calculated and compared to each other.

Case 1

When the boiler was operating at its setpoint value, the output value of the 5 trained faults was zero. This indicates that at this point the boiler has no-fault

Case 2

When the value of any of the inputs deviated from the setpoint, the system checks and returned a result which showed that fault has crept in. The magnitude calculation showed the size of the fault. The explanation facility of the programme alerts the operator of the type of fault, location, and cause. The operator can further check what to do immediately to mitigate the fault so that work will not be interrupted. The GUI enables the operator to see what is happening as the process goes on.

IV. CONCLUSION

From the generated result, an increase in temperature of the overheated steam, super-heatedsteam pressure, and a decrease in cooling water flowrate in the boiler signified boiler overheating. Increase/decrease in feedwaterflowrate at the standard value of feed water pressure in the boiler signifiedboiler feed pump failure and increased flowrate of fuel oil increases combustion in the boiler, which resultsin to increase in temperature and pressure build-up and result to high-pressure trip in the boiler.

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