American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-8, Issue-12, pp-44-52
www.ajer.org
Research Paper Open Access

Computerization of Gas Turbine Performance Using Gas Path Analysis and Artificial Intelligence

[1]Odokwo, V. E and [2]Izuka, R. C
[1]Akwa Ibom State University, Ikot Akpaden, Akwa Ibom State; Nigeria. Department Of Marine Engineering
[2]Maritime Academy Of Nigeria, Oron, Akwa Ibom State; Nigeria. Department Of Marine Engineering
Corresponding Author Tel: Victor Effiong Odokwo.

ABSTRACT : *It is desirable engineering wise to monitor GT performance and diagnose faults before the damage is done since the fault can cause permanent damage to the components. Condition monitoring for preventive maintenance proves to be a better way considering the longer run. This research work describes how modern gas-path analysis and artificial intelligence can be used as a tool for GT condition monitoring and diagnosis. Various type of artificial intelligence was studied and fuzzy logic was found to be a very suitable method for GT diagnosis because of the fuzzy logic set rules. In this work, fuzz logic was implemented in MATLAB environment to predict the degree of fault in the GT through its Gas path analysis. The linguistic variables used as inputs are temperature, pressure and shaft speed while the linguistic variable used as output is failure. The universe of discourse for temperature is [0, 55], pressure is [0, 1000], shaft speed is [0, 5000] and failure which is the fault is [0, 1]. A type fuzzy logic model and the center of gravity method are used as the defuzzification module. From the results it is seen that the value for the highest possible fault is 0.909 at point 8 on the y axis.*

KEYWORDS: a*rtificial intelligence, computerization, condition monitoring, gas path, gas turbine, matlab*

Date of Submission: 25-11-2019 Date of acceptance: 07-12-2019

I. INTRODUCTION

Gas turbine (GT) is a turbo-machinery that uses the gaseous energy of air to convert chemical energy of fuel into mechanical energy. The GT has three main components - the compressor, the combustion chamber and the turbine. The rotating blade of the turbine performs a dual function of driving the compressor via the shaft to draw in more compressed air into the combustion chamber and also spin the generator to produce power. The GT has many advantages ranging from high power to weight ratio compared to reciprocating engines, reduced vibrations, good power rating, fewer moving parts and high operational speed (Odokwo and Ogbonnaya, 2019). Despite these advantages, their sensitivity to defects that causes deterioration are important because the influence of these defects can be critical to the proper operation which in turn affects the overall performance of the GT . The operating parameters appearing along the engine's gas path are flow, pressure, temperature and shaft rotational speed. The changes that occur in the gas path parameter can be used to identify the deterioration of the component that may occur during operation thereby decreasing the down time of the engine (Diakunchak, 1992). This work is hinged on the application of artificial intelligence (AI) for GT performance monitoring and targets the detection of core engine deterioration through gas path parameters analysis. Gas path (GP) analysis technique is used to access the condition of individual component based on the aero-thermodynamic relationship that exists between components and involving direct measurement of gas path parameters. The aero- thermodynamic relationship deals with conditions where there is significant heat exchange in the gases or a significant thermal effect between the gases and solid surfaces, in this case, the compressor, combustor and the turbine (Jasmani et al., 2011). The presence of gas path physical fault induces changes in the component characteristics that show up a deviation of the measurable parameter from the base line conditions. The purpose of GP analysis is to detect, isolate and quantify the gas path component faults that have observable impact on the measurable variable to facilitate the subsequent isolation of the underlying physical fault (Kruz and Brun, 2001). AI is a term used for simulated intelligence in machines. The ideal characteristic of AI is its ability to rationalize and take action that has the best chance of achieving a specific goal (Kruz et al., 2009) This methodology offers the opportunity to make a more accurate and detailed maintenance schedule to minimize shut down time, save maintenance cost, increase availability and reliability.

II. METHODOLOGY

The GT under study is a PG9171 model manufactured by general electric. It operates at a speed of 5000rpm with an output of 132MW and is used for electric power generation. The GT has an efficiency of 34.6%, the maximum and minimum ambient temperatures are 267K and 326K respectively.

Mathematical Model of The GT System

For the purpose of this research, figure 1 shows the schematic diagram of the GT plant used for the modeling.

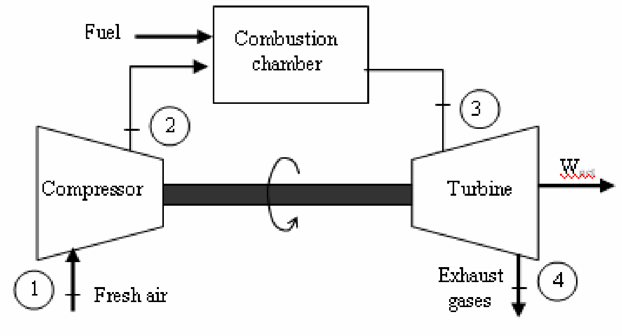

Figure 1 Schematic diagram of a GT plant

The concept applied is based on GP analysis and AI. This relies on performance parameters trending at standardized conditions so that it can be compared to actual performance. As discussed earlier, a deviation in the measured gas parameters can be accounted because of the deviation in component health (Provost, 1994). The approach to this research is primarily quantitative which will be based on:

i. Analyzing the GT based on the aero thermodynamic relationship between gas path components and gas path measurable parameter.
ii. To develop an algorithm to solve the problem
iii. Use fuzzy logic tool box in MATLAB to predict the degree of fault in the GT components.

To obtain the component performance parameter, the gas path measurable parameter will be gotten using the technical descriptions of the GT. The relationship between gas path measurable parameters according to Odokwo and Ogbonnaya of the work done in the compressor is given by :

$$W_{gc} = m_a C_p T_1 \left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1 \right) \quad (1.1)$$

The expression for the work done, W_{gt} by the turbine is:

$$W_{gt} = m_a C_p T_4 \left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1 \right) \quad (1.2)$$

The heat supplied, Q_{sg} to the system is obtained by the relations below:

$$Q_{sg} = m_a C_p \left(T_3 - T_1 P_r^{\left(\frac{\gamma-1}{\gamma}\right)} \right) \quad (1.4)$$

The network done by the topping cycle is derived from the expression below:

$$W_{net\,.gas} = W_{gt} - W_{gC} \quad (1.5)$$

According to Odokwo and Ogbonnaya and from the above, the efficiency of the gas turbine is:

$$\eta_{gas\,.tur} = \frac{\left[m_a C_p \left(T_3 - \left(\frac{T_3}{P_r^{\left(\frac{\gamma-1}{\gamma}\right)}} \right) \right) - m_a C_p T_1 \left(P_r^{\left(\frac{\gamma-1}{\gamma}\right)} - 1 \right) \right]}{m_a C_p \left(T_3 - T_1 P_r^{\left(\frac{\gamma-1}{\gamma}\right)} \right)} \quad (1.6)$$

Application of Gas Path to the GT

In this research, the application of GP analysis to the measurable operating parameters - temperature, pressure and shaft speed are treated as dependent parameters while the gas path component - compressor, combustor and turbine are treated as independent parameters. The GP analysis algorithm in use can be summarized into the following main steps: (i) measurement normalization (ii) reference value generation (iii) estimation of performance deviation, and (iv) diagnosis decision. This algorithm was introduced by Urban in 1969 (Sajeev, 2015). The GP analysis method is based on thermodynamic relationships where one of the main objectives is to estimate deterioration in gas path components from a number of measured sensor signals which are denoted as measurement deltas (Δ) (Urban. 1992). The linear relationship between the measured signals and the engine health parameters is written in the expression:

$$\Delta Y = X\Delta x + c \tag{1.7}$$

Elements in ΔY are: spool speeds ΔN, temperatures ΔT, and pressures ΔP. Elements in Δx are: efficiencies Δη, and flow capacities ΔΓ of the gas path components such as compressors, turbines, and fans. The matrix X can be divided into two parts: An engine fault influence matrix Xe, a sensor fault influence matrix Xs, where the previous defined matrix X and health parameter Δx in equation (3.10) is extended with the sensor fault dependencies (Volponie et al., 2003). To simplify the mathematics, the sensor measurement noise vector is assumed to be Gaussian with a zero mean.

Health parameters

Compressor Health Parameter

$$S_{FC}\,F_C = \frac{Gc,cor,deg}{Gc,cor} \tag{1.8}$$

$$\Delta\, S_{FC,}\,F_C = \frac{(Gc,cor,deg - Gc,cor)}{Gc,cor} \tag{1.9}$$

$$S_{FC}\,E_{ff} = \frac{\eta_c,deg}{\eta c} \tag{1.10}$$

$$\Delta S_{FC}\,E_{ff}\,\frac{(\eta_c,deg - \eta c)}{\eta c} \tag{1.11}$$

Combustor Health Parameter

$$S_{FB}\,E_{ff} = \frac{\eta_B,deg}{\eta_B} \tag{1.12}$$

$$\Delta S_{FB}\,E_{ff} = \frac{\eta_B,deg - \eta B}{\eta_B} \tag{1.13}$$

The performance of actual combustor can be expressed as follows:

$$\eta_B deg = \vec{f}(load, \Delta S_{FE}\,E_{ff}) \tag{1.14}$$

$$S_{FT}\,F_c = \frac{(GT,cor,deg)}{GT,cor} \tag{1.15}$$

$$\Delta S_{FT}\,F_c = \frac{(GT,cor,deg - GTcor)}{GT,cor} \tag{1.16}$$

$$S_{FT}\,E_{ff} = \frac{(\eta T,deg)}{\eta T} \tag{1.17}$$

$$\Delta S_{FT}\,E_{ff} = \frac{\eta T,deg - \eta T)}{\eta T} \tag{1.18}$$

Application of Fuzzy Logic to the Proposed Research Project

Fuzzy logic is a method used to formalize the human capability of imprecise reasoning. Such reasoning represents the human ability to reason approximately and judge under uncertainty. It provides a system of non-linear mapping from an input vector into a scalar output. This work uses type-1 fuzzy logic algorithm proposed by Prof. Lofti Zadeh in1965. The fuzzy logic model used in this work is presented in figure2:

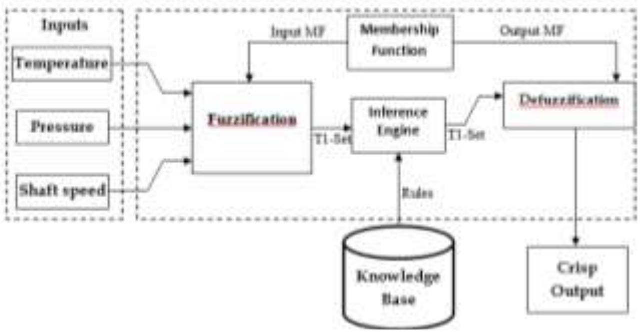

Figure 2 fuzzy logic model used for the computerization of the GT performance

Membership Function: This is a mathematical equation that helps the fuzzification module convert the crisp input into a fuzzy set. The type of membership function used in this work is the triangular membership functions.

Membership Functions (MF)

The MF parameters used in this work was collected from Ibom Power Station, Akwa Ibom State. It comprises the membership function type, linguistic variable associated with each group of functions, their universe of discourse, and fuzzy linguistic terms.

i. Linguistic Variable/Universe of Discourse

The linguistic variables and the universe of discourse (range of values for each variable) used in this work is presented below:

Table I: Universe of Discourse

Linguistic Variable	**Universe of Discourse**	**Description**
Temperature	[0, 55]	Temperature (input variable)
Pressure	[0, 1000]	Pressure (input variable)
Shaft Speed	[0, 5000]	Shaft Speed (input variable)
Failure Ure	[0 1]	Failure Probability (Output Variable)

Membership Function Model

This work makes use of the triangular membership function. This function is presented mathematical as shown below;

$$f(x;a,b,c) = \begin{cases} 0\,, & x \le a \\ \frac{x-a}{b-a}\,, & a \le x \le b \\ \frac{c-x}{c-b}\,, & b \le x \le c \\ 0\,, & c \le x \end{cases} \qquad (1.19)$$

Expert's Membership Function Values

The MF values control the shape of the membership function. Each membership function used in this work has three (3) control points. These values are presented below in table II:

Table II: Membership function values for temperature {0 55}

TERMS	A	B	C
Low	0	0	22
Moderate	5.5	27.5	49.5
High	33	55	55

Table III: Membership function values for Pressure {0 1000}

TERMS	A	B	C
Low	0	0	400
Moderate	100	500	900
High	600	1000	1000

Table IV: Membership function values for Shaft Speed {0 5000}

TERMS	**A**	**B**	**C**
Low	0	0	2000
Moderate	500	2500	4500
High	3000	5000	5000

Membership Function (MF) Plot

This is the diagrammatic representation of a membership function. These plots are a representation of the membership function values presented above. The MF plot is a curve that defines how each points in the input space is mapped to a membership value. The membership function plots for the linguistic variable are shown in section 3.1 to 3.4.

Inference Engine

The inference engine is a component of the system that applies logical rules to the knowledge base to deduce new information. This process would iterate as each new fact in the knowledge base could trigger additional rules in the inference engine. A Mamdani type inference mechanism proposed in 1975 by Ebrahim Mamdani is used in this work. The evaluation of rules against our fuzzy set is done using the following model:

$$f^{i}(x') = \mu_{\tilde{F}_1^i}(x') * \dots * \mu_{\tilde{F}_1^i}(xp') \qquad (1.20)$$

The Mamdani inference engine expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification.

Defuzzification

Defuzzification is the process of producing a quantifiable result in fuzzy logic system given fuzzy sets and corresponding membership degrees. It is the process that maps a fuzzy set to a crisp set. These will have a number of rules that transform a number of variables into fuzzy result, that is, the result is described in terms of membership in fuzzy sets (Ying et al., 2016). The deffuzification technique used in this system is called centroid. This technique is given by the relation:

$$COG = \frac{\sum_x^b \mu_A(x)x}{\sum_x^b \mu_A(x)} \qquad (1.21)$$

Where $\mu_A(x)$ is the degree of membership of x in a set A

Membership Function Plot for Temperature

From Table II, the membership function plot for temperature shows that the value of the linguistic term "low" having three points A, B and C are 0, 0 and 22 respectively. For the linguistic term "moderate", the values for the three point A, B and C are 5.5, 27.5 and 49.5 respectively. For the linguistic term "high", the values of the three points A, B & C are 33, 55 & 55 respectively. The MF plot gotten from table II for temperature is shown in figure 3:

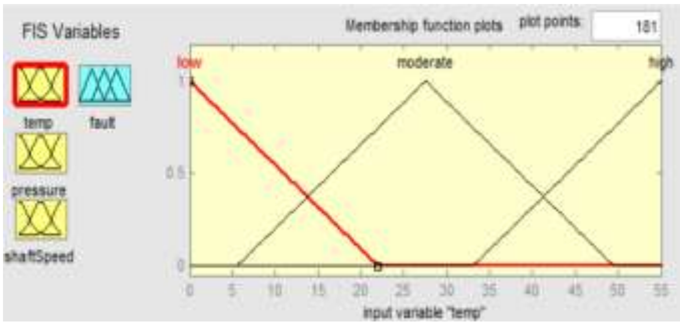

Figure 3: Membership function plot for temperature

Membership Function Plot for Pressure

From table III, the membership function plot for pressure shows that the values for the linguistic term "low" for the three points A, B & C are 0, 0 & 400 respectively. For the linguistic term "moderate", the values of the points A, B & C are 100, 500 & 900 respectively. For the linguistic term "high" the values of the points A, B & C are 600, 1000 & 1000 respectively. The MF plot gotten from table 3.3 for pressure is shown in figure 4:

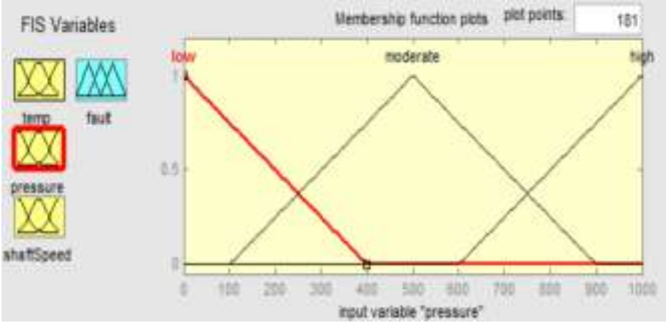

Figure 4 Membership function plot for Pressure

Membership Function Plot for Shaft speed

From table 4, the membership function plot for shaft speed shows that the values for the linguistic term "low" for the 3 points A, B & C are 0, 0 & 2000 respectively. For the linguistic term "moderate" the values of the points A, B and C are 500, 2500 & 4500 respectively. For the linguistic term "high", the values for the three point A, B &C are 3000, 5000 respectively. The membership function plot for shaft speed gotten from table 4 is presented below;

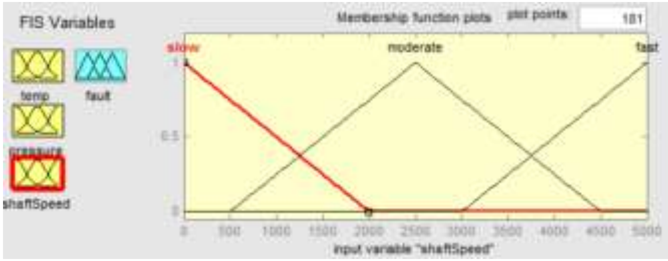

Figure 5: Membership function plot for Shaft Speed

Membership Function Plot for Failure

The MF plot for failure is presented in figure 6:

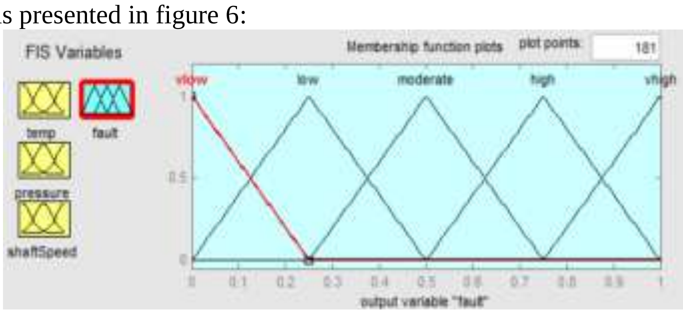

Figure 6: Membership function plot for Failure

Fuzzy Rule

The number of rules used in this system is 27, calculated as $\text{Terms}^{\text{Variables}} = 3^3 = 27$. The fuzzy rule shows the combination of the MF terms used to determine the extent of the fault and generate five linguistic terms in the fault probability which are very low (VL), low (L), moderate (M), high (H) and veryhigh (VH).

III. RESULTS

The prediction result is carried out through the process of defuzzification. The defuzzification technique used in this system as stated ealier is the COG defuzzification technique. This technique is given by the formula stated in equation 3.25 and shown in table V.

Table V: Fault {0,1}

S/N	Temperature	Pressure	Shaft speed	Fault
1.	6.3	307	452	0.217
2.	14.9	416	934	0.36
3.	20.9	524	1360	0.391
4.	30.2	657	3100	0.552
5.	36.1	753	3460	0.638
6.	40.1	849	3890	0.725
7.	47.4	898	4370	0.871
8.	52.7	898	4370	0.909
9.	3.64	898	4370	0.721
10.	24.8	452	4370	0.725
11.	24.8	452	452	0.25
12.	24.8	580	1900	0.48
13.	39.4	777	4250	0.727
14.	18.9	295	4250	0.591
15.	40.8	488	693	0.412

Temperature Plot

This plot shows the different temperature values used in model testing. From the prediction result in figure 4.1 it can be seen that the temperature values (y axis) is between 0 to 60 and the data count (x axis) is between 1 to 15. The highest temperature is at point 8, which is 5.27 and the lowest temperature is at point 1 which is 6.3.The temperature plot is presented in figure 7:

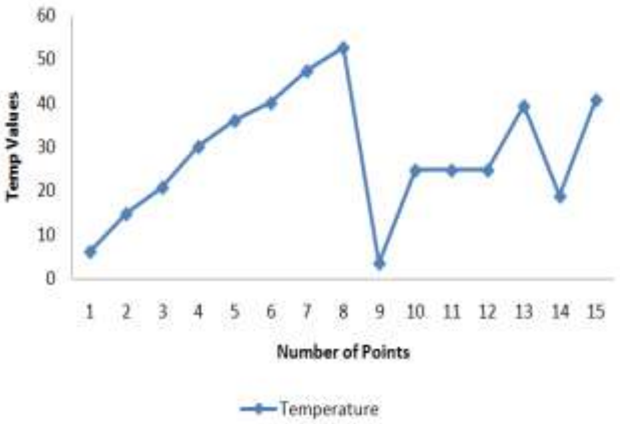

Figure 7: Temperature Plot

Pressure Plot

For the pressure plot, the highest pressure is at point 7, 8 and 9 (x axis) which is 897 (the highest value of pressure at the y axis) while the lowest pressure is at point 14 (x axis) which is 295 (the lowest value of the pressure at the y axis). The pressure values used in the work during system testing is presented in figure 8:

Figure 8 Pressure Plot

Shaft Speed Plot

For the shaft speed plot, the highest value of shaft speed at point 7, 8, 9, 10 (x axis) is 4976 (y axis) and the lowest value for the shaft speed is at point 1 (x axis) is 452 (y axis). The shaft speed value used in the work during system testing is presented in figure 9

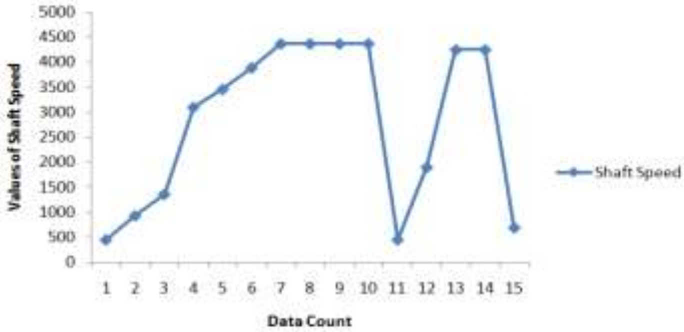

Figure 9: Shaft Speed Plot

Fault Prediction Result

The fault prediction values (y axis) is taken between 0 and 1 and the number of points (x axis) is taken between 1 to 15. From the result in figure 11, it can be seen that the value for the highest possible fault (y axis) is 0.909 which is at point 8 on the x axis.

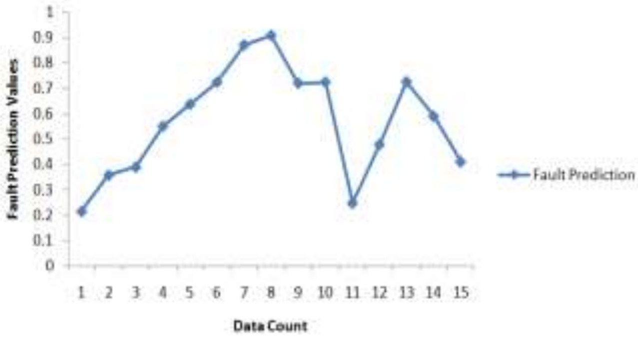

Figure 11 Fault Prediction Result

Effect of Input Parameters on Fault

The input parameters as stated earlier are temperature, pressure and shaft speed and the output is the fault. Figure 12 shows the graphical representation of the input parameters on fault.

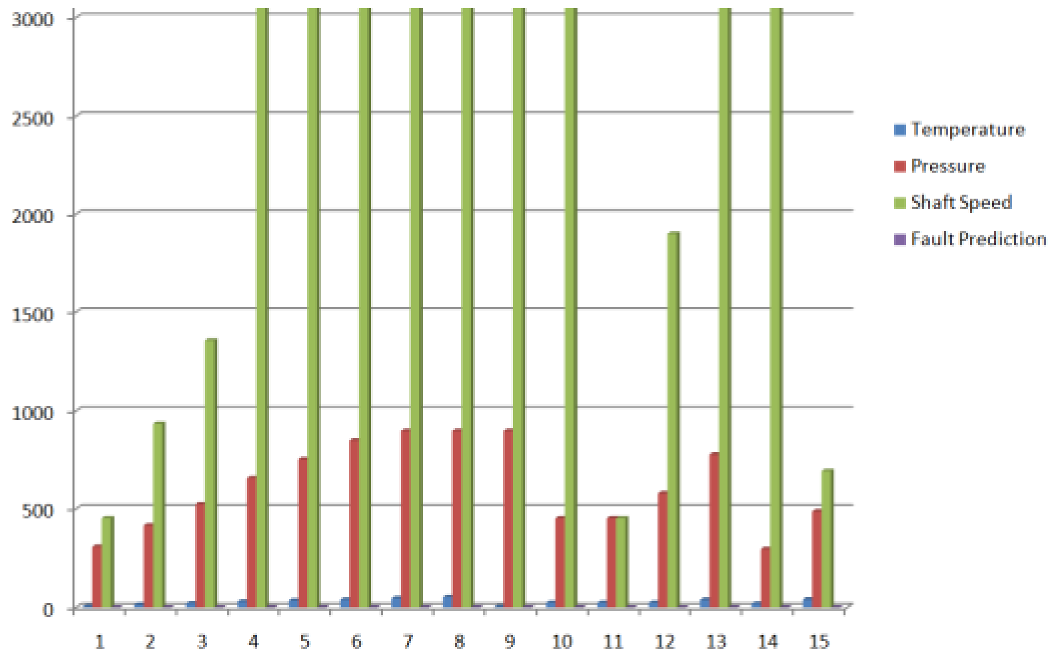

Figure 12 Effect of input on Output (Fault)

IV. CONCLUSION

In this work, fuzzy logic utilizing gas path analysis is applied in studying, analysis and predicting parametric performance and GT component deterioration. Fuzzy logic presented a very reliable methodology for condition monitoring of the GT components for effective fault detection and consequentially ensuring a robust preventive maintenance strategy to forestall break down. For this model, the parametric prediction are almost unbiased and have minimal variance giving a very satisfactory limits. To this effect, GPA and artificial intelligence is the way forward to better operation of a gas turbine both in marine and other applications.

REFERENCES

[1]. Deopold H.R., and Gas, F.D. (1999). The Application of Expert Systems and Neural Networks To Gas Turbine Prognosis and Diagnosis. ASME paper 98-GT-101. Journal of Engineering forGas Turbines and Power,Trans ASME, 121,601,612.
[2]. Diakunchak I. S. (1992).Performance Deterioration in Industrial Gas Turbines.Journal of Engineering for Gas Turbines and power, 114(2); 161-168
[3]. Jasmani M.S; Li Y.G and Z. Ariffin, (2011). Measurement Selection For Multicomponent Gas Path Diagnostic Using Analytical Approach and Measurement Subset Concept. Journal of Engineering and Gas Turbine Power, 133(11).
[4]. Kruz R. and Brun K. (2001).Degredations In Gas Turbine Systems. Journal of Engineering for Gas Turbines and Power, (123)1: 70-77.
[5]. Kruz R., Brun K. and Wollie M (2009).Degredation Effects On Industrial Gas Turbines. Journal of Engineering for Gas Turbines and Power. 131(6).
[6]. Odokwo V. E. and Ogbonnaya E. A. (2019). Performance optimization of combined gas and steam power plant using artificial neural network. Indian Journal of Engineering, 16, 35-45
[7]. Sajeev A.M (2015).Gas Turbine Diagnosis Based on Gas Path Analysis.Delft University of technology.
[8]. Urban, L.A. (1992).Gas Path Analysis Applied to Turbine Engine Condition Monitoring.AIAA-72-1082.
[9]. Volponi A.J., Deopold H., and Ganguli R., (2003). The Use of Kalman Filters and Neural Network Methodologies in Gas Turbine Performance Diagnostics: A comparative study. Journal of engineering for gas turbine and power,125(4):917-924.
[10]. Ying Y., Yunpeng C., and Shuying Li. (2016). Study On Gas Turbine Engine Fault Diagnostic Approach with a Hybrid of Gray Relation and Gas Path Analysis.Advances in Maechanical Engineering, vol 8(1) 1-14.

Victor Effiong Odokwo. "Computerization of Gas Turbine Performance Using Gas Path Analysis and Artificial Intelligence" American Journal of Engineering Research (AJER), vol. 8, no. 12, 2019, pp 44-52