Fault Analysis and Prediction in Gas Turbine using Neuro-Fuzzy System

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Abstract - *In the modern aviation industry, gas turbine engines play important role in in the aircraft design. However, because of the complex nature of the design and operation of such engines, there is need to constantly monitor and maintain the engines to perform at its best. One of the most challenges aspects of such engines is the detection of fault as it can occur at any instance. Thus, detecting the fault and predicting it occurrence is of paramount important. In this paper, a novel technique of detecting and predicting faults in a gas turbine engine using a robust Neuro-Fuzzy controller. The gas turbine mathematical model is design and validated analytically. The fault detection and prediction system are then designed using the Neuro-fuzzy technique and validated through simulation study. The results obtained shows that the Neuro-Fuzzy system was able to predict when the gas turbine is in error by checking with the train signal on the relay with a high signifying the detection of fault and 0 otherwise. In addition, the Neuro-Fuzzy controller outperformed the PID controller, and this can be attributed to the fact the Neuro-fuzzy has the ability to train and correct the error based on the previous training results.*

Key Words: Dynamic modelling, Gas turbine, Fault detection, Mu-Law compressor, Neuro-fuzzy controller, PID controller.

1.INTRODUCTION

In our world today, gas turbine engines play important role especially in the aviation industry, mechanical drivers, and power generation [1]. Gas turbine engine also known as combustion turbine is a type of combustion engine consisting of a compressor, combustor, and turbine with a basic operation based on the Brayton circle [2]. It has been in existence since 1500 and continuous to evolve till today. The basic operation of the gas turbine based on Brayton circle is shown in Fig. 1 [3]. From the figure, the gas turbine normally follows four thermodynamic processes namely compression (isentropic), combustion (isobaric, constant pressure), and isentropic expansion and heat rejection.

Based on the above description, different researchers have been involved in designing gas turbine engines of recent due to advancement in technology. This is done in order to improve the system performance and reliability. Areas that seen increase in research is mainly in the detection and analyzing of faults from different aspects of the engine processes.

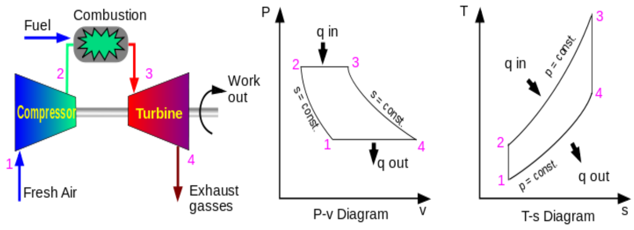


Fig -1: Gas turbine engine based on Brayton cycle [3].

The most notable works includes that of Waleligne et al [3] where a general review on gas turbine condition-based diagnosis was presented. They did by looking at different diagnostics methods and their advantages and disadvantage in the gas turbine engines. In [4], a stride in the engine performance by altering the engine fuel control framework, altering power turbine (PT) nozzle guide vane (NGV) and compressor inlet guide vane (IGV) are keys qualities was presented. Their technique was able to the turbine inlet temperature thereby increasing the turbine efficiency. In [5], a fault isolation technique in gas turbine engine based on component qualification was presented. The approach was able to determine which component (subsystem, system) is failing or has failed, and which kind of fault mode existed. Also there are other NDT and fault detection techniques available which are well established and applicable in multiple industrial sectors [6, 7, 8], however, their approach needs to be correlated with watched reaction to a defective condition which reduces the efficiency.

With the advancement in the use of neural network, different techniques have been proposed to make the fault detection intelligent by detecting and predicting the occurrence and location of faults in the engine processes. This can be seen in the work of Stephen et al [9] where the use of neural network in detecting and predicting fault was proposed. Their idea was based on a proof of concept which was verified in [10] through simulation study. In [11], Gas Turbine Fault Diagnosis Using Probabilistic Neural Networks (PNN) was proposed using three different classification methods compared with the PNN and the technique was able to predict the future occurrence of faults in gas turbines. In [12], a neural network-based scheme for fault detection of an aircraft engine. using a set of dynamic neural networks (DNN) was developed to detect fault occurrence in the engine. Despite the advancement in the use of neural network in detecting fault in gas turbine engine, majority of the techniques so far are complex, expensive, and too slow to train the system. In this work, a novel technique using neuro-fuzzy is presented that is robust, simple, and fast in detecting and predicting fault in gas turbine engine. are developed to learn the dynamics of the jet engine.

The remaining part of the paper is organized as follows: Section 2 presents the fault detection technique used to detect the fault at different stages in the gas turbine engine, Section 3 deals with the results analysis and discussion, and section 4 deals with the summary and conclusion of the work.

2. FAULT DETECTION IN A GAS TURBINE

In this section, the research method adopted for the design and simulation of the gas turbine system is discussed. The model will be developed based on the Brayton cycle model. The mathematical model of the system is designed first after which the model will be verified analytically. Thereafter, the model will be validated through numerical simulation. The intelligent controller system using Neuro-fuzzy is then designed after which the system will compared with PID controller method to show the efficacy of the Neuro-fuzzy controller in analyzing and predicting faults in a gas turbine system. The summary of the methodology is shown in Fig. 2.

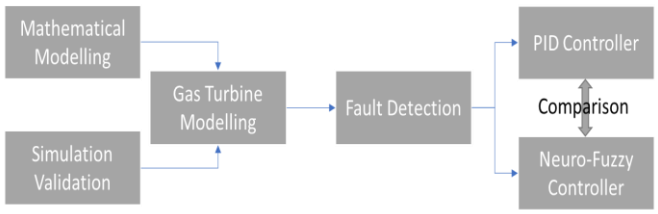


Fig -2: Block diagram of the methodology adopted for this work.

2.1 Gas Turbine Modelling

To model a gas turbine, the design is mostly based on Brayton cycle design as shown in Fig. 1. From the figure, the gas turbine consists of a compressor, combustor, and turbine. The process starts by first taking an air through the air inlet and the air get compressed at the compressor whose main function is to increase the inlet air pressure. It then goes through the Combustion Chamber where a fuel is then sprayed in a continuous manner to ignite the air to make the combustion to produce a High flow Temperature. The next stage is sending the high pressure and high temperature gas to enter the turbine section which in turn sends energy to the turbine blades making them to rotate. Through this process, an electricity can then be generated.

2.2 Simulink Design for Fault Detection System

Based on the above model, the relationship between the compressor and the shaft can be expressed in terms of the rotor dynamics using the energy balance equation given by [13]

$$\frac{dE}{dt} = \eta_{mec} W_T - W_C \quad (1)$$

Where E is the energy, t is the time, η_{mec} is the efficiency, and W_T and W_C are the work done in the turbine and the compressor respectively.

In terms of the volume dynamics, the relationship between the input and the output of the gas turbine can be expressed using

$$\dot{P} = \frac{RT}{v}\left(\sum \dot{m}_{in} - \sum \dot{m}_{out}\right) \quad (2)$$

Where P is the pressure, T is the temperature, R is the gas constant, V is the volume, and is the mass flow rate.

The above relationships can then be used to model the gas turbine in Simulink as shown in Fig. 3 adopted from [14].

2.3 Simulink Design for Fault Detection System

After modelling the gas turbine, in real life, fault can occur in the gas turbine and a system to detect and analyse it is needed. In most gas turbine design, fault detection mechanism/technique are added to know when the system is operating normally or not. To do this, a method to detect the fault is developed and then integrated into the gas turbine model developed in Section 2.1. this is done to detect faults in the system, and it is an important and effective tool when operators want to change from preventive maintenance to predictive maintenance with the goal of reducing the maintenance cost. In this study, the Mu-law compressor and the thermocouple function are used to model a technique of detecting fault in a gas turbine. The design of this technique is done in Simulink as shown in Fig. 4 (adopted from the work in [15]). From the figure, the atmospheric air goes through the engine through the air inlet modelled as step input in the Simulink. Thereafter, a reference filter is used to mitigate for any error as a result of dust from the air. This is modelled using a transfer function shown in the figure. The next stage is the compressor design based on Mu-Law with internal circuit design as shown in Fig. 5.

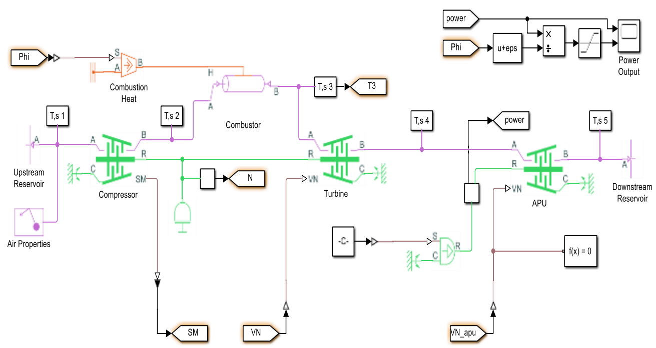


Fig -3: Simulink design of the gas turbine engine based on Brayton cycle design.

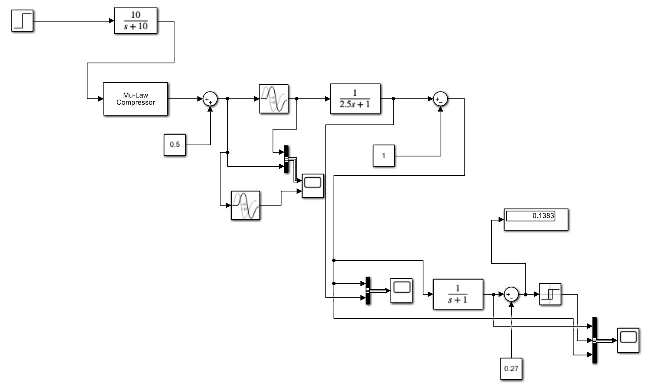


Fig -4: Simulink design of the fault detection technique in gas turbine system.

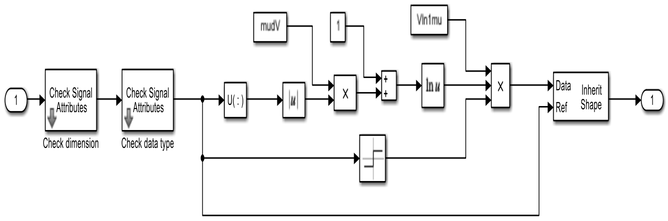


Fig -5: Simulink internal design of the Mu-Law compressor.

As shown in Fig. 4, the compressor is then connected to the combustor and the exhaust using variable delay blocks as shown. A summer is used to add the gas constant which is 0.5 for our case. Their output can then be viewed on a scope to show the present operational stage of the gas turbine. The combustor delay output is then connected to a temperature transfer function which is then linked to a relay to be switching between when a fault is detected. Once a fault is detected, the information from the relay is then compared with original message to know when there is a fault based on a threshold set and for our case, the error should not go beyond 0.271, else, a fault is detected.

From the above design a controller is needed to be design that can be used to control the gas turbine system and the design is presented in the next section.

2.4 Design of a Neuro-Fuzzy Controller System

For the controller design, due to advancement in the use of gas turbine engine especially in the modern aircraft, an intelligent controller is needed. In the literature, there are different techniques of design intelligent controllers such as the works in [16]. In this work, we adopted the Neuro-fuzzy controller based on the Adaptive Nuero-fuzzy Inference system (ANFIS) due to its simplicity and its ability to train the system fast using the artificial neural network (ANN). In addition, a PID controller is design to compare the ANFIS design and the PID controller to show the efficacy of the system. To model the controller using the ANFIS, there are four stages involved namely Fuzzification, Rule evaluation (inference), Aggregation of the rule outputs (composition), and Defuzzification as shown in Fig. 6 [17].

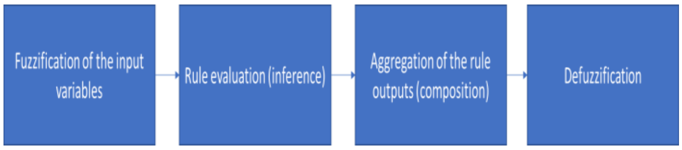


Fig -6: Stages in the design of the Neuro-fuzzy controller.

In the Fuzzification stage, the crisp inputs are defined. In the gas turbine, faults occur based on three different scenarios namely fuel flow rate fault F1, fault at the exit temperature F2, and fault at the turbine output torque F3. These three faults are used as the crisp input to create the membership functions as shown by the fuzzy design in 7.

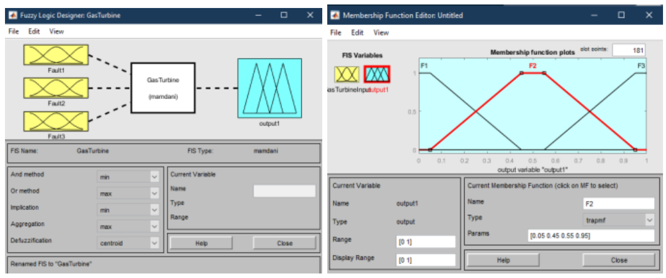


Fig -7: Fuzzy design and its membership function.

The next stage is to add the rules governing the fault detection and the fault can be detected based on the conditions shown in Table 1. The table parameters are added as rule governing the fuzzy design which can then be imported in ANFIS. The rule is set to flag 1 whenever a fault is detected with the position of the 1 indicating which fault is detected. When there is no fault, the condition is 0.

Table -1: Rules Evaluation table.

Condition	Residue (R1)	Residue (R2)	Residue (R3)
Normal	0	0	0
Fault 1	1	0	0
Fault 2	0	1	0
Fault 3	0	0	1

Using the above table, the aggregation is done after viewing the rule after which the output id defuzzied into the ANFIS as shown in Fig. 8.

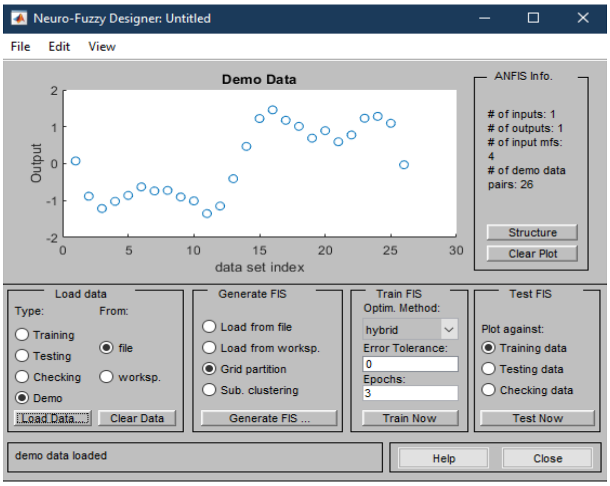


Fig -8: Neuro-Fuzzy design.

The neuro-fuzzy controller design is shown in Fig. 9 and the Simulink design for the modified fault detection technique including the neuro-fuzzy controller is shown in Fig. 10.

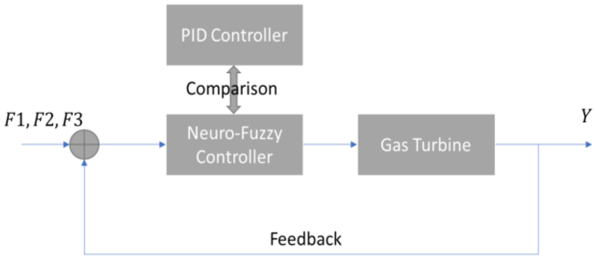


Fig -9: Neuro-Fuzzy controller block diagram.

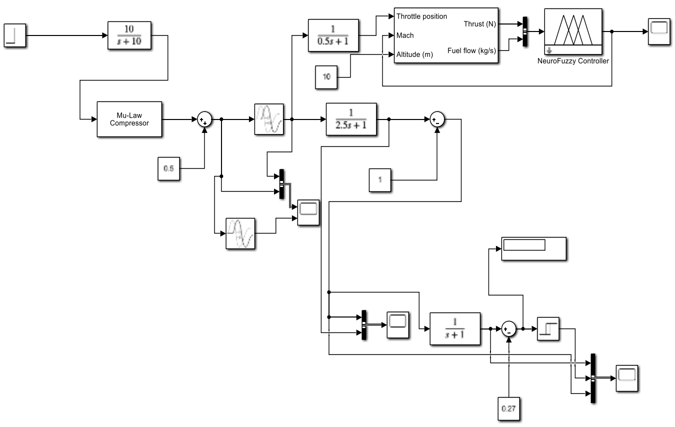


Fig -10: Overall design for the fault detection and prediction using Neuro-Fuzzy controller.

The simulation results are presented in the next section.

3. RESULTS AND DISCUSSION

In this section, the simulation results based on the methods described in section 2 are presented. The results start by first validating the model developed for the gas turbine through simulation in MATLAB/Simulink platform. Thereafter, the model developed to detect the fault is simulated and validated using performance measures such as roto speed, load angle and temperature entropy diagram. The neuro-fuzzy controller results are then compared with the conventional PID controller to show the efficacy of the technique developed.

3.1 Simulation Set Up and Parameter Definitions

For the gas turbine, the simulation parameters were set based on the Brayton Cycle settings with the following configurations: Compressor, alternator, and turbine mass flow rate of $1e^{-6}\ kg/s$, power of the turbine 100 kW, the system inputs are configured based on the parameters shown in the plot in Fig. 11. Based on these settings, the simulation of the gas turbine can then be carried out with the results presented in the next section.

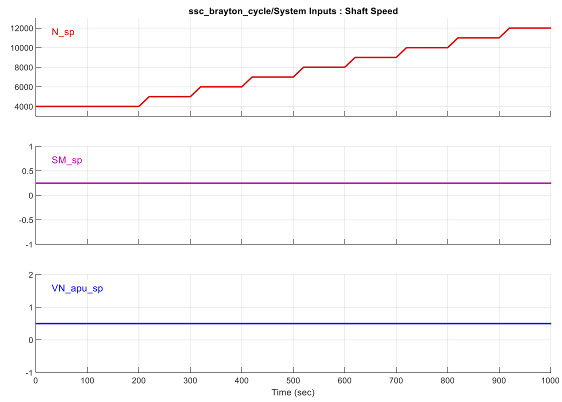


Fig -11: System inputs configuration for the gas turbine.

3.2 Simulation Results of the Gas Turbine System

Using the model developed in section 2 for the gas turbine, the simulation was carried out and the results are presented as shown in Fig. 12. From the results, the validation of the model is done by studying the output power and the efficiency of the machine. From the results, it can be seen that for the output power, the power was low signifying the onset of the machine where the compressor is compressing the air converting to high pressure, then to the turbine to get high temperature before the power is being generated at a time of around 500 seconds. The machine then started generating power in a step sequence until it stabilises at around 100 kW which is the maximum power of the turbine. For the efficiency of the system, it is low at the beginning before it also increases as the machine started generating power although the efficiency needs to be improved because it is a bit low likely due to some fault in the system. Thus, integrating the gas turbine with fault detection and prediction capability is paramount.

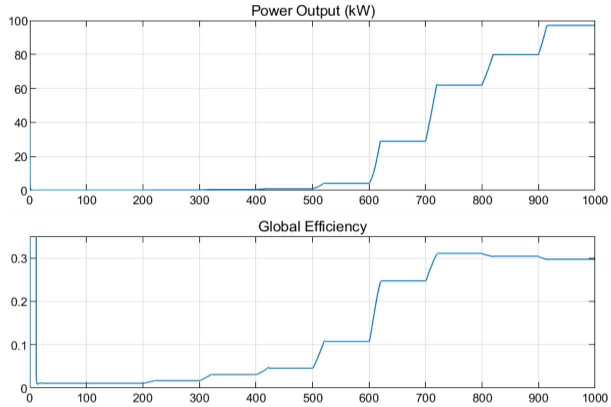
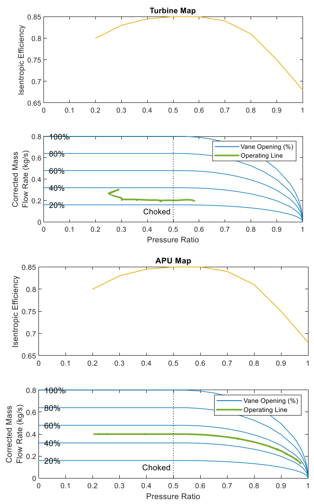


Fig -12: Results for the output power and efficiency of the gas turbine.

In addition, the turbine, and the auxiliary power unit (APU) characteristic for the gas turbine are shown in Fig. 13. From the results, it was observed that for the turbine, it can be choked off at around 30% based on the operating line while for the APU, it is choked at around 50%. This indicates that the turbine needs improvement in the design.



(a) (b)

Fig -13: Results for the (a) Turbine and (b) APU.

3.3 Simulation Results of the Fault Detection and Prediction using Neuro-Fuzzy System

Based on the simulation result of the gas turbine, to detect the existence of any fault in the system, the modified neuro-fuzzy controller system in Fig. 10 is used. The simulation was run to test the operating condition of the gas turbine which can be monitored by observing combustor and the exhaust delays plot from the scope in Simulink and the results are shown in Fig. 14. From the figure, it could be observed for both the combustor and the exhaust delays, the step input response can be clearly seen to be working with little ripples at the edges when it is switching to high values.

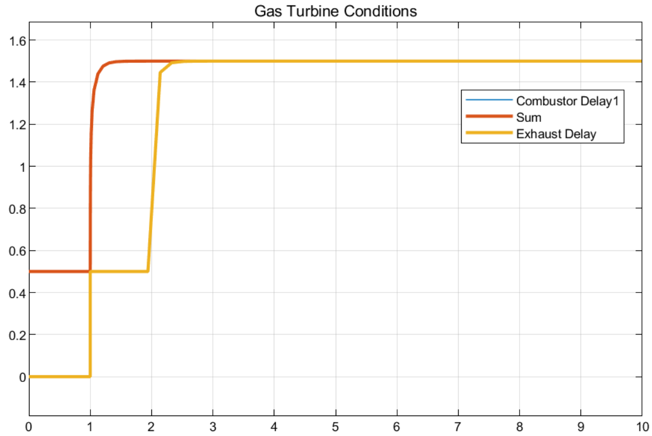


Fig -14: Results for the exhaust and combustor delays of the gas turbine engine.

For the fault detection and as shown by Fig. 10, a relay is added to detect the fault by switching to high (1) when the any of the 3 faults is detected and zero otherwise. The results for the fault detection with fault and the corrected version using Neuro-Fuzzy is shown in Fig. 15. From the results, it can be seen that an error was detected by the relay which the Neuro-fuzzy quickly detect and correct the output to the closer value of the relay. The error can then be mitigated as shown from the result. In addition, the intelligent system can next predict whether in the turbine is in error by always checking with the train signal which on the relay when it is high signifying the detection of fault and 0 otherwise.

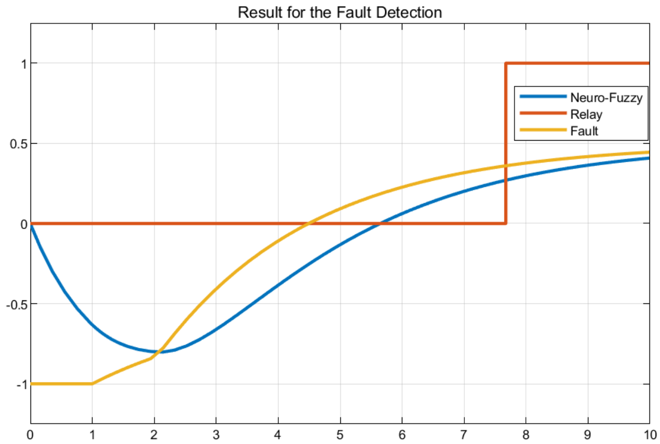


Fig -15: Results for the detection of fault using Neuro-fuzzy controller.

3.3 Comparison between Neuro-Fuzzy and PID Controller

To show the efficacy of the neuro-fuzzy controller, the results obtained is compared with a conventional PID controller having the Simulink design shown in Fig. 16 adopted from the work in [18]. The controller is used to control the speed regulator, temperature regulator, and surge margin regulator as shown in the figure. It is incorporated in the gas turbine model design and the simulation was run with the results shown in Fig. 17.

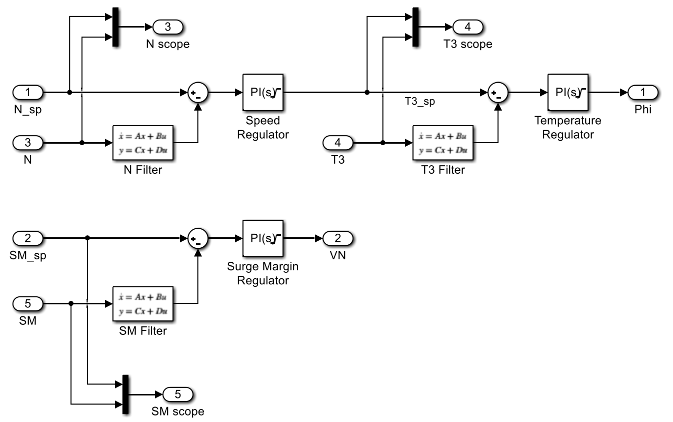


Fig -16: PID controller Simulink design for the gas turbine.

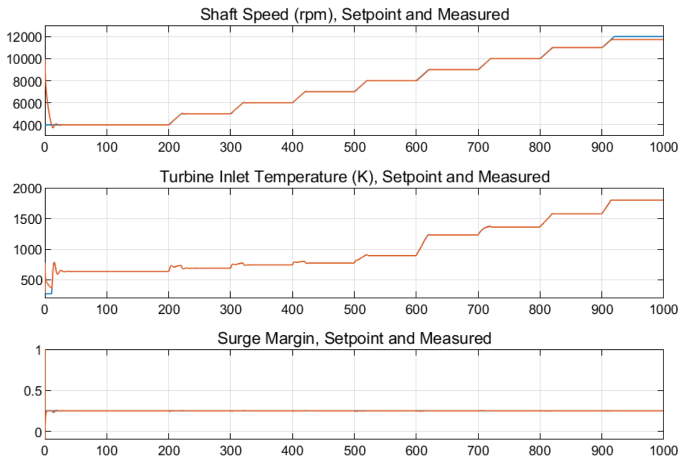


Fig -17: PID controller simulation results for the gas turbine.

Based on the PID controller design and the simulation validation, the two controllers were simulated together for the gas turbine fault detection and the results are shown in Fig. 18. From the result, it can be seen that in terms detecting and correcting the error, the Neuro-Fuzzy controller outperform the PID controller, and this can be attributed to the fact the Neuro-fuzzy has the ability to train and correct the error based on the previous training results. Thus, it can be concluded that using intelligent controllers such Neuro-fuzzy offers better result in detecting and predicting fault in gas turbine engine compared to the conventional PID controller.

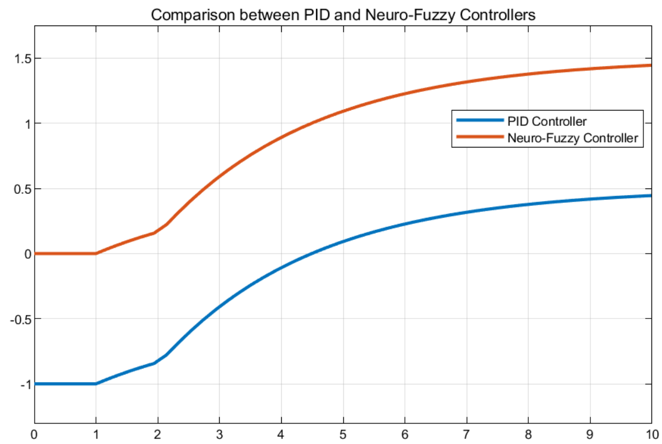


Fig -18: results for the comparison between the Neuro-Fuzzy and the PIC controller for the gas turbine.

4. CONCLUSIONS

In conclusion, this paper presented a novel technique of detecting and predicting faults in a gas turbine engine using a robust Neuro-Fuzzy controller. At first, the gas turbine was modelled based on the components of compressor, combustion, and turbine. The mathematical model was developed based on this and verified analytically. Thereafter, a Neuro-fuzzy controller and PID controller were designed and used for comparison. Simulation results obtained showed the efficacy of the Neuro-Fuzzy controller over the conventional PID controller. From the results, From the results, it was shown that an error was detected by the relay which the Neuro-fuzzy quickly detect and correct it. The intelligent system was able to predict whether in the turbine is in error by always checking with the train signal which on the relay when it is high signifying the detection of fault and 0 otherwise. In addition, the Neuro-Fuzzy controller outperformed the PID controller, and this can be attributed to the fact the Neuro-fuzzy has the ability to train and correct the error based on the previous training results. Thus, it can be concluded that using intelligent controllers such Neuro-fuzzy offers better result in detecting and predicting fault in gas turbine engine compared to the conventional PID controller.

REFERENCES

[1] K. Young, D. Lee, V. Vitali, and Y. Ming, "A fault diagnosis method for industrial gas turbines using bayesian data analysis," Journal of Engineering for Gas Turbines and Power, vol. 132, Article ID 041602, 2010.

[2] M. P. Boyce, Gas Turbine Engineering Handbook, 4th ed., Oxford: Butterworth-Heinemann Ltd, ELSEVIER Science & Technology, 2011, 1000 pp.

[3] Waleligne Molla Salilew, Zainal Ambri Abdul Karim, Aklilu Tesfamichael Baheta, Review on gas turbine condition-based diagnosis method, Materials Today: Proceedings, 2021.

[4] S. Sanaye, S. Hosseini, Off-design performance improvement of twin-shaft gas turbine by variable geometry turbine and compressor besides fuel control, Proc. Inst. Mech. Eng. Part A J. Power Energy 234 (7) (2020) 957–980.

[5] A. M. Y. Razak, Industrial Gas Turbines: Performance and Operability, first ed., Cambridge, England: Woodhead Publishing Limited, 2007, 602 pp.

[6] Sunny AI, Zhao A, Li L, Kanteh Sakiliba S. Low-cost IoT-based sensor system: A case study on harsh environmental monitoring. Sensors. 2021 Jan;21(1):214.

[7] Sunny AI, Zhang J, Tian GY, Tang C, Rafique W, Zhao A, Fan M. Temperature independent defect monitoring using passive wireless RFID sensing system. IEEE Sensors Journal. 2018 Nov 21;19(4):1525-32.

[8] Tang C, Rashvand HF, Tian GY, Hu P, Sunny AI, Wang H. Structural health monitoring with WSNs. Wireless Sensor Systems for Extreme Environments: Space, Underwater, Underground, and Industrial. 2017 Aug 7:383-408.

[9] S. S. Tayarani-Bathaie, Z. N. Sadough Vanini and K. Khorasani, "Fault detection of gas turbine engines using dynamic neural networks," 2012 25th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), 2012.

[10] G. V. Beard and M. R. Rollins, "Engineering Economics," in Power Plant Engineering, V. Black, Ed., Springer Science & Business Media Inc., 1996.

[11] Duk, "Wikimedia Commons Webpage," 2013. [Online]. Available: http://en.wikipedia.org/wiki/File:Brayton_cycle.svg. [Accessed 14 June 2013].

[12] H. Cohen, G. Rogers and H. Saravanamut, Gas Turbine Theory, 5th ed., Pearson Education, 2001.

[13] H. Asgari, X. Q. Chen and R. Sainudiin, "Considerations in Modelling and Control of Gas Turbines - A Review," in the 2nd International Conference on Control, Instrumentation, and Automation (ICCIA 2011), Shiraz, Iran, 2011. R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[14] W. Rachtan and L. Malinowski, "An Approximate Expression for Part-Load Performance of a Micro Turbine Combined Heat and Power System Heat Recovery Unit," Energy, vol. 51, pp. 146-153, 2013.

[15] L. Malinowski and M. Lewandowska, "Analytical Model-Based Energy and Exergy Analysis of a Gas Microturbine at Part-Load Operation," Applied Thermal Engineering, vol. 57, no. 1-2, pp. 125-132, 2013.

[16] A. G. Memon, K. Harijan, M. A. Uqaili and R. A. Memon, "Thermo-Environmental and Economic Analysis of Simple and Regenerative Gas Turbine Cycles with Regression Modeling and Optimization," Energy Conversion and Management, vol. 76, pp. 852– 864, 2013.

[17] S. M. Hosseinalipour, E. Abdolahi and M. Razaghi, "Static and Dynamic Mathematical Modeling of a Micro Gas Turbine," Journal of Mechanics, vol. 29, no. 2, pp. 327-335, 2013.

[18] S. M. Hosseini, A. Fatehi, A. K. Sedigh and T. A. Johansen, "Automatic Model Bank Selection in Multiple Model Identification of Gas Turbine Dynamics," Journal of Systems and Control Engineering, vol. 227, no. 5, pp. 482-494, 2013.

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