World Journal of Engineering Research and Technology
WJERT
www.wjert.org SJIF Impact Factor: 5.924

ENGINE COMPONENT FAULT DIAGNOSTICS USING ARTIFICIAL NEURAL NETWORK

***Diwa James Enyia**

Department of Mechanical Engineering, Cross River University of Technology, P.M.B 1123, Calabar, Nigeria.

Article Received on 20/06/2023 **Article Revised on 10/07/2023** **Article Accepted on 30/07/2023**

***Corresponding Author**
Dr. Diwa James Enyia
Department of Mechanical Engineering, Cross River University of Technology, P.M.B 1123, Calabar, Nigeria.

ABSTRACT

Power generation in Nigeria has been on the increase over the last decades, since most of the hydraulic resources that are used to drive the hydropower plants have already been deployed. In order to keep electrical energy at affordable prices, several modalities have been considered, such as reduction in operating and maintenance costs of thermoelectric facilities. On this ground, engine component fault diagnostic technique are intended to enhance maintenance quality, reduce engine downtime, and thereby increasing plant availability, while maximising operational profit by keeping engine efficiency at standard level. In this technical research, an artificial neural network ANN based fault diagnostics technique have been developed to assess the health condition of a single shaft heavy duty engine ALSTOM GT11N2. The engine employed was modelled using software known as PYTHIA 2.8, where actual engine data was used in the matching process, afterwards, component parameters degradations were applied to the model to generate neural network training and validation samples. Finally, a three level nested structure was established comprising fault detection, isolation, and quantification functions, each represented by specific neural network architecture. Which are trained to tackle both measurement data without and with noise. In the earlier case, the individual networks presented excellent performance, while in the latter case, good performance have been achieved, despite a few problems with the fault isolation network. Nonetheless, the whole nest neural networks have presented good and acceptable performance respectively when analysing these two cases.

KEYWORDS: *Artificial Neural Network, Engine Health Monitoring, Engine Simulation, Gas Path Analysis, Heavy Duty Engine, Nest Neural Network.*

1. INTRODUCTION

The year 2016 saw an improvement in Nigeria electricity supply from 3500 to 4232.6MW which is about 17% increase.[1] The electricity supply is made up with 86% from thermal power and 16% from hydro supply.[2] Predictably, hydro based electricity generation is at the mercy of the seasons. During dry season, the water level in hydro power plant reservoirs drops, getting close to their lower operational safety limit. In order to avoid operational problems at facilities and an energy shortage in the grid, the integrated electricity system (IES) intensifies the use of thermal generation at these period.

The impact of seasonal weather phenomena on energy supply is nothing new and has been affecting hydro power plants operational patterns since their activation. But this has been taken over by electric energy consumption, with the construction of several thermal power plants, which were initially used to complement electricity supply during dry season. AFAM phase II in river state, Nigeria is one of the largest thermal power stations, with electricity generation installed capacity of about 1000MW.[2] The desire to reduce overall costs has led to a thorough optimization project of this thermoelectric park, composed of several areas, where condition based maintenance presents an ideal opportunity for sizeable cost reduction.

The aim of this technical research is to provide a fault diagnostics tool, based on artificial neural network (ANN) techniques, which is able to perform the component fault analysis of a single shaft heavy duty gas turbine, herein represented by an ALTOM GT11N2 engine. The methodology consist the use of PYTHIA software to match the engine model with actual parameters, and to utilise this model to generate ANN training and validation samples. In addition, MATLAB was also used to create each individual ANN and the algorithm of the nest neural network, which is used to perform gas turbine component fault diagnostics analyses.

2. Heavy Duty Gas Turbine Fault Diagnostics Systems

The need for industrial gas turbine (IGT) such as prime movers of rotating machines or for power generation has been on the increase in the last decade. The engines are either aero-derivative or heavy duty. The engine health monitoring systems (EHMS), which was initially developed for use with aero engines, has been successfully applied in IGT's. This intrinsic approach to improving the availability of the system and reducing maintenance costs has been studied since the early days of the gas turbine industry, though its practical implementation has only become possible due to relatively recent developments in data acquisition and processing technologies.[3]

The reliability of gas path component such as compressor, combustor, and turbine is considerably higher than other systems. Their long downtime leads to a reduction in availability.[4]

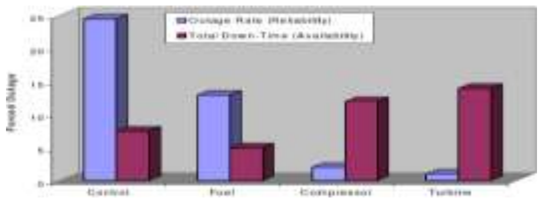

Figure 1: Reliability and availability of gas turbine system.[4]

Figure 1 presents a comparison between the reliability and availability of four different gas turbine components, where the least reliable element is the control system, while the element with the lowest availability is the turbine, though it has a lower outage rate, and therefore higher reliability. In addition, the EHMS is also used for certain performance recovery procedures, such as compressor cleaning, where it is possible to carry out an economic evaluation of the intervention in order to maximise revenue and minimise maintenance cost. The main benefits of applying gas path diagnostic techniques are: equipment life enhancement, reduction of spare parts, improvement in maintenance management quality, optimisation of engine overhaul, identification of the economic breakeven point to conduct engine intervention, improvement and optimisation of instrument, and maximisation of power plant availability.[5] Summarily, the utilisation of fault diagnostics systems in gas turbine industrial facilities has become indispensable. The techniques that have been developed for aero as turbine engines are suitable for industrial applications, and can be practically implanted due to constant hardware development, which also allows the development of new techniques that require higher data process capacity. The benefits of gas path diagnostic applications are related to a variety of aspects, such as economic evaluation, hazard identifications, production and maintenance optimisation.

3. Gas Turbine Components Fault Diagnostics systems

The gas path components of the engine comprise of the compressor, turbine, and the combustor. The latter will be omitted in this study since its efficiency does not change considerably over time, and a characteristic that is needed for gas path fault detection system (GPFDS). The most frequent faults leading to a reduction in the performance parameters of gas path components are: fouling, tip clearance, erosion, corrosion, and object damage.[6] These features indicate that there is a relationship between changes in independent parameters, that is, component health conditions, and dependent parameters, such as those relating to performance. In addition, different component faults affect performance parameters in different ways, and can be considered as fault signatures. However, it should be noted that different faults can have similar signatures, thereby, necessitating a combined diagnostics approach to properly identify the cause of a problem.

Fault diagnostics methods are categorised into two ways viz: conventional and involving. The former comprises visual inspection, fault tree, fault matrix, vibration analysis, and GPA. The latter includes artificial intelligence based methods, such as fuzzy logic, GA, and ANN. Currently, GPA is the most common set of techniques applied to assess the health of gas path components. GPA techniques include linear-GPA, non- linear GPA, weighted least square algorithms, Kalman filters, and adaptations of these methods using artificial intelligence techniques. Although these methods have been demonstrated as suitable for the application, they rely heavily on the quality of measurements.[5] Artificial Neural Network is applied in this research and it is a numeric approximation of a function, where the logic of the relationship between input and output is unknown. Its framework is based on the basic human learning models, which is essential for GPA.

4. Measurement Analysis

The techniques mentioned above rely on the quality of measurements. Since the parameter measurement deviation set is the source of information of any fault diagnostic technique, measurement error must be no more than a fraction of its deviation due to engine degradation. However, each measurement contains error, which can be related to instrument uncertainty or variation of the measurement value over the actual value in order to use it.[7]

5. Fault Diagnostics Application

A new method for performing GT component fault diagnostics through the estimation of degraded engine performance parameters, and engine health parameters from measurement data was first devised by Li.[7] Lipowsky et al[8] developed an alternative performance degradation detection technique to cope with single fault events. Bouguet & Leonard[9] presents an engine performance monitoring system based on Kalman Filter KF that uses a residual treatment technique to enhance the capability of isolated fault detection. Kurz & Brun[10] have studied the influence of multiple component degradation on engine performance parameters. Vodopianov[11] presents a probabilistic approach of GPA. The technique comprises a fault coefficient matrix, where each element is given by a probability density function (PDF). It is claimed to overcome the lack of accuracy of linear methods, and the complexity of non- linear methods.

6. Artificial Neural Network

This concept was first introduced by McCulloch & Pitts[12] in an attempt to reproduce the human brain's signal processing system. Although models developed to date are yet to fully represent any actual biological structure, they are able to perform complex calculations based on neuroscience principles, such as numerous highly connected simple processing units, adaptable connections, and parallel processing.[13] ANN has been applied in pattern recognition, image processing, empirical modelling, optimization, control systems and data processing.[14] ANN application for solving complex problems is extremely attractive in principles, though in practice there are numerous issues to be addressed prior to its successful implementation. First, the architecture of an ANN comprises several figures, which account for the distinct number of layers, connections, neurons, and transfer functions. Secondly, an ANN can be updated or trained by synchronous or asynchronous, deterministic or stochastic process. Finally, an infinite combination of ANNs can be used to solve a specific problem. These questions are inter-connected and must be answered together during the process of ANN creation.[15]

7. Types of Architecture of ANN

The architecture of ANN is defined by the combination of neurons, number of layers and transfer functions. The optimum configuration of an ANN for a specific application can only be found by trial-and-error, where convergence is achieved by an incremental increase in the number of neurons.[16,17]

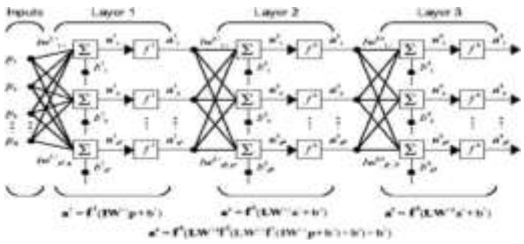

Figure 2: Schematic Model of Multi-layers ANN.[18]

A multilayer ANN is as represented in figure 2. Each layer is composed of biases, transfer functions, summation and multiplication operators, and weight matrix. The weight and biases is determined during the training process. It has been shown that a one hidden layer ANN with sufficient number of neurons can be used as a good representation of any continuous function.[16,17] There is also double and single layers ANN.

8. ANN Fault Diagnostics Application

ANN has been applied to GT component diagnostics through various approaches. ANN has been used based on measurement data sets to estimate the deviation between clean and degraded engine measurements[17,19]; it has also been applied to sensor fault classification and missed measurement recovery.[16,20] Ogaji and Singh[21] applied nest neural network techniques. Donat et al[22] presents an investigation of the advantages of using data reduction and classifiers fusion technique to increase the performance of the fault diagnostics data- driven methods. Shivakumar et al[23] assess the influence of operational parameters and fuel composition on the performance and emissions of a single cylinder diesel engine. A brief revision of the importance of GT fault diagnostics and the method hitherto developed were introduced based on ANN.[21]

9. Nest Neural Network Methodology

It is composed of engine model simulation, nest ANN architecture, individual neural network creation and validation method, and fault diagnostics analysis workflow. PYTHIA 2.8 was first used to simulate the clean and degraded engine design point model. Latter, a suitable nesting architecture was drawn to perform the detection, isolation, and quantification of engine component faults. Afterwards, individual neural networks, with different architectures were created to represents each function of the nest ANN. In addition, four validation methods were developed to assess the quality of the neural networks. Finally, a generalised workflow of a computational programme code was developed to allow its implementation in MATLAB language.

10. Engine Model Simulation

PYTHIA 2.8 was used to simulate the engine. The software is based on TURBOMATCH, a successful GT engine simulation tool develop by Cranfield University, in United Kingdom, which uses component maps matching technique to perform engine simulation. The engine operating parameters extracted from an actual installation through PI (Plant Information) software were used to determine the engine reference point that would be used as an engine model design point. No strict criteria was used to select this point, though a careful observation of available data was needed in order to select a condition likely to occur several times throughout the operation time range.

Since this model is built for fault diagnostics purpose, the error between the target parameters and the simulation results may not exceed a fraction of the deviation parameter, which is given by the difference between a specific degraded engine measurement and one for a clean engine. Eventually, using PYTIA Simulation mode, engine components degradations, covering the model domain, are applied to the model, yielding a set of measurement parameters for each condition. These results are further used as neural network training samples. This operation can also be carried out using PYTHIA 2.8 to develop neural network training samples generation.

11. Industrial Gas Turbine Application

The engine applied for the simulation is an industrial gas turbine ALSTOM GT11N2, which comprises one compressor, one turbine mounted on the same shaft, and one top mounted silo combustor. The compressor consists of 16 stages and 3 IGVs and produces a pressure ratio of about 16:1. The turbine consists of 4 stages that are able to produce 115MW of net power. A brief description of the engine is as shown in table 1 below;

Table 1: ALSTOM GT11N2 Main Features.[24]

Fuel	Natural Gas	
Frequency	Hz	60
Gross Electrical Output	MW	115.4
Gross Electrical Efficiency	%	33.9
Gross Heat Rate	kJ/kWh	10619
Turbine Speed	rpm	3600
Compressor Pressure Ratio	-	15.9:1
Exhaust Gas Flow	kg/s	400
Exhaust Gas Temperature	°C	526
NOx Emissions	vppm	<25

12. PYTHIA Engine Model Application

The engine model was used to simulate an actual GT engine ALSTOM GT11N2 located at AFAM phase II, a portharcourt thermal power station in Nigeria. Operational data collected from the engine through PI were used to set up the design point model. The design point model refers to as operational condition likely to occur during the engine’s operating campaign. The set of measurements used to set up the engine model comprises ambient temperature, compressor exit temperature, shaft power, gas flow, fuel flow and turbine inlet temperature.

Figure 3: GT1N2 Engine.[14]

A schematic representation of the engine is as could be seen in figure 3, while the PYTHIA interface structure is as shown in figure 4 with 8 bricks, which are intake, compressor, burner, mixer, turbine, duct, convergent nozzle and performance.

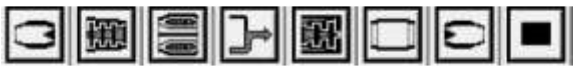

Figure 4: PYTHIA Engine Model Interface.

The comparison between the actual engine operating data and engine model simulated data is as shown in table 2 below. It can be observed that the error between actual and simulated values of the ambient temperature, compressor exit temperature, turbine inlet temperature, compressor exit pressure, shaft power, and gas flow do not exceed the absolute values of 0.02%, while error between actual and simulated values of the turbine exit temperature and fuel flow do not exceed the absolute value of 0.08%. Therefore, the engine design point model can be considered a good representation of actual engine measurement at the specific reference point.

Table 2: Design Point Model Matching Results.

Measurement	Unit	Operational Data	Simulation Data	Error
Ambient Temperature	[K]	297.9	298.0	0.00%
Compressor Exit Temperature	[K]	674.9	674.8	-0.01%
Turbine Inlet Temperature	[K]	1358	1358	-0.02%
Turbine Exit Temperature	[K]	809.8	810.5	0.08%
Compressor Exit Pressure	[atm]	13.52	13.52	0.02%
Shaft Power	[W]	1.068E+08	1.068E+08	-0.02%
Gas Flow	[kg/s]	398.57	398.56	0.00%
Fuel Flow	[kg/s]	6.966	6.963	-0.04%

13. Degraded Engine Model Behaviour

A drop in flow capacity and efficiency was applied to the ANN training during the engine simulation for the compressor, turbine, and the combination of both components respectively in other to simulate the component degradation. The drops for flow capacity ranges from 0.0% to -0.5%, while that of compressor efficiency ranges from 0.0% to 5.0%. The behaviour of the compressor exit temperature under degradation is as shown in figure 5. It indicates an increase in compressor exit temperature as the absolute value of compressor efficiency drop increases. On the other hand, it shows a decrease in compressor exit temperature as the absolute value of flow capacity drop increases. It is suitable for use as a measurement parameter in the compressor fault diagnostic system since it is sensitive to both compressor efficiency and flow capacity drop.

There is a slight decrease in turbine exit temperature as the absolute value of compressor efficiency drop increases. On the other hand, it shows an increase in turbine exit temperature as the absolute value of flow capacity drop increases as could be seen in figure 6.

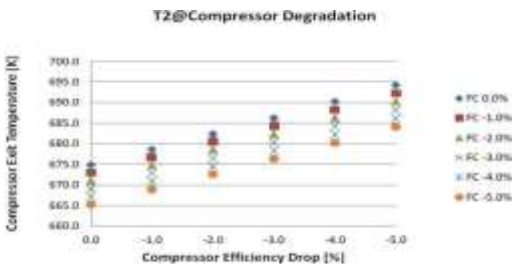

Figure 5: Compressor exit temperature under compressor degradation.

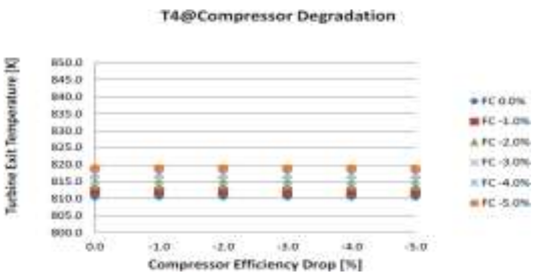

Figure 6: Turbine exit temperature under compressor degradation.

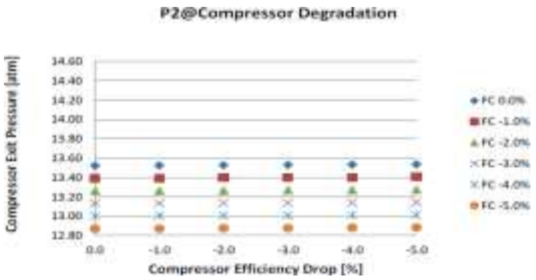

Figure 7: Compressor exit pressure under compressor degradation SHP@ Compressor degradation.

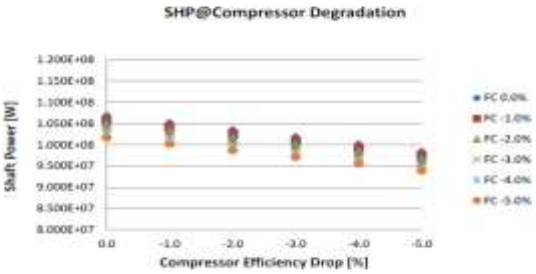

Figure 8: Shaft power under compressor degradation.

Figure 7 shows that compressor exit pressure does not change as the compressor efficiency drop changes. On the other hand, it shows an abrupt decrease in compressor exit pressure as the absolute value of flow capacity drop increases. It can also be seen that shaft power decreases as the absolute value of compressor efficiency drop increases as can be seen in figure 8. The tendency can be noted as the absolute value of flow capacity drop increases.

The percentage fault implanted for compressor is the same as that on the turbine. It shows a slight increase in compressor exit temperature as the absolute value of turbine efficiency drop increases as shown in figure 9. On the other hand, it shows a decrease in compressor exit temperature as turbine flow capacity drop increases.

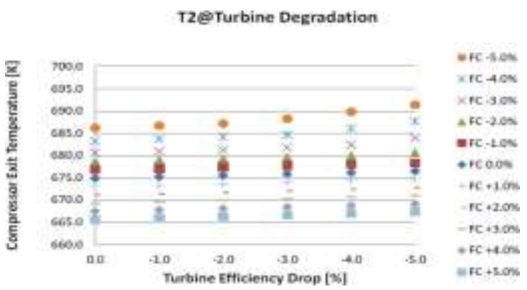

Figure 9: Compressor exit temperature under turbine degradation.

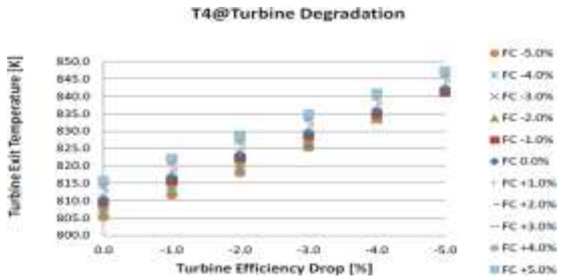

Figure 10: Turbine exit temperature under turbine degradation.

It can be seen in figure 10 that there is an increase in turbine exit temperature as the absolute value of turbine efficiency drop increases. The same behaviour was observed as turbine flow capacity drop increases.

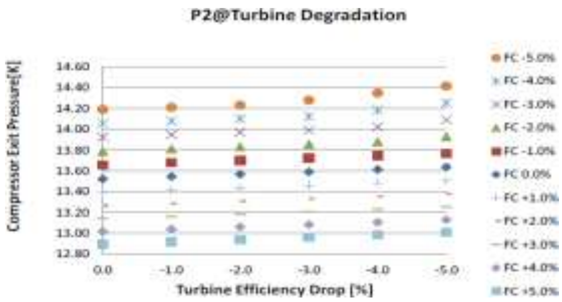

Figure 11: Compressor exit pressure under turbine degradation.

It shows a slight increase in compressor exit pressure as the absolute value of turbine efficiency drop increases. On the other hand, it shows a decrease in compressor exit pressure as turbine flow capacity drop increases as shown in figure 11.

It is also noted in figure 12 that there is a decrease in shaft power as the absolute value of turbine efficiency drop increases. On the other hand, it shows an increase in shaft power as turbine flow capacity drop increases. Since this parameter is sensitive to both turbine efficiency drop and turbine flow capacity drop, it is suitable for use as a measurement parameter in the turbine fault diagnostics system.

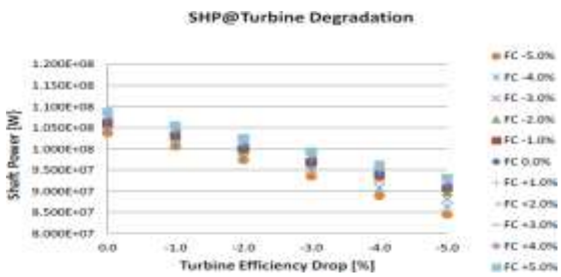

Figure 12: Shaft power under turbine degradation.

14. Nest Neural Network Validation

This is presented in two cases; measurement parameter with noise, and without noise. The nest neural network comprises of 5 individual ANNs, which are one single layer perceptron ANN used to detect whether or not the engine is degraded, one probabilistic ANN used to isolate the fault, that is, it is used to find out whether the compressor or turbine are degraded. Lastly, three multiple layer feed forward ANNs are used to estimate the seriousness of the fault.

The nest neural network validation process consists of the validation of each individual ANN, and the nest neural network itself. Degradation detection ANN accuracy is assessed by its percentage of error. Fault isolation ANN accuracy is assessed by the RMS of each case error percentage. Compressor fault quantification ANN accuracy is assessed by the RMS of compressor flow capacity drop estimation error and compressor efficiency drop estimation error, for each point of the domain. Turbine fault quantification ANN accuracy is assessed by the RMS of turbine flow capacity drop estimation error and turbine efficiency drop estimation error, for each point of the domain.

The measurement parameter set for the case without noise or bias comprises compressor exit temperature, turbine exit temperature, compressor exit pressure, and shaft power. The measurement parameter deviation vector considered the clean engine measurement vector as the base line.

The map of RMS error of the training process of compressor fault quantification ANN is as presented in figure 13. The majority of the domain presents RMS error up to 0.02%, exceeding the requirements of the diagnostic results. The right low corner of the domain presents a slight high RMS error, nearly 0.2%, which is also suitable for this kind of analysis. Therefore, the training process of the compressor fault quantification ANN has succeeded.

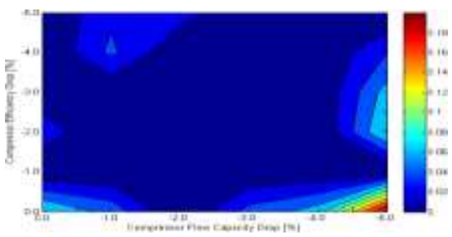

Figure 13: Compressor fault quantification ANN training RMS error.

Figure 14 presents the map of the RMS error of the validation process of compressor fault quantification ANN. The left side of the map presents RMS error around 0.08%, with points of 0.12%. The centre and right side of the domain presents RMS error around 0.03%. The right low corner presents RMS error around 0.1%. Though there are differences in the accuracy level throughout the domain, the compressor fault quantification ANN can be considered suitable for performing the compressor fault diagnostic.

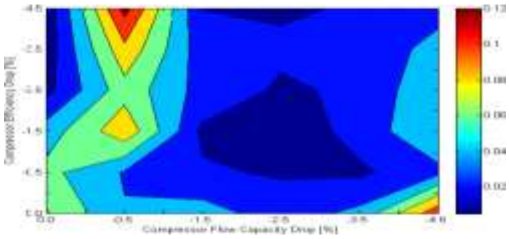

Figure 14: Compressor fault quantification ANN validation RMS error.

Since training input and target vectors has been created, the compressor fault quantification neural network can be established using the MATLAB neural network tools. Both training and validation samples are used to assess accuracy of the ANN. The former assess the quality of the training process, and the later assess the ANN's performance. A similar training as that of the compressor was applied for the turbine fault quantification validation with the use of MATLAB neural network.

Figure 15 presents a map of the RMS error of the training process of turbine fault quantification ANN. The majority of the domain presents RMS error up to 0.01%, which by far meets the requirements of the diagnostic results. The right side of the domain presents a slightly high RMS error, around 0.05%, which is also suitable for this kind of analysis. Therefore, the training process of the turbine fault quantification ANN has succeeded.

The map of the RMS error of the validation process for turbine fault quantification ANN is shown in figure 16.

The centre and left side of the map presents RMS error of about 0.01%, with points of 0.005%. The right side of the domain presents RMS error of about 0.02%, with points of 0.03%. The right low corner presents RMS error of about 0.035%. Though there are differences in the accuracy level throughout the domain, the turbine fault quantification

ANN can be considered suitable for performing the turbine component fault diagnostics.

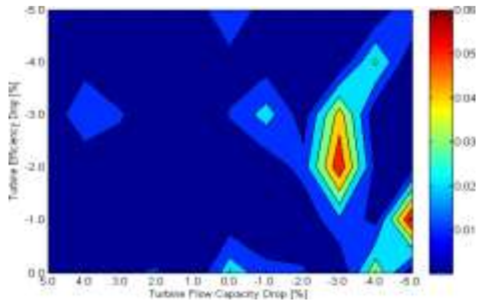

Figure 15: Turbine fault quantification ANN training RMS error.

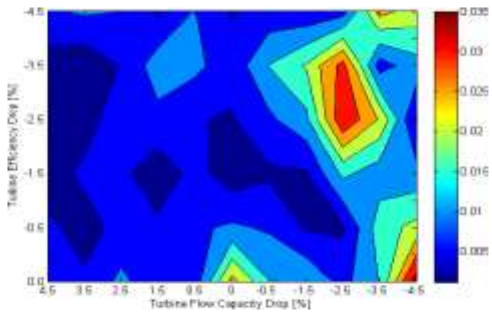

Figure 16: Turbine fault quantification ANN validation RMS error.

A test case using measurement ***with noise*** was applied to the nest neural network. Both training samples and validation samples with and without noise. These samples were initially free of measurement error, but given noise through a statistic method using MS Excel spread sheet. The nest neural network accuracy is firstly verified by the accuracy of the individual ANN that forms it, and then the complete nest structured is also assessed. The ANN output vector was then compared to the desirable output. The degraded detection ANN accuracy was assessed using the respective ANN to simulate the components that comprise the validation samples, yielding 0.7% of error, while the training samples yielded 0.1% error. Therefore, this ANN can be considered suitable for performance diagnostics analysis.

For the training process assessment of the fault isolation ANN when using measurement samples with noise, the fault detection error for the compressor, turbine, and combined are 13.6%, 6.9%, and 1.2% respectively, with RMS error of 8.8%. Both component fault detection fail rate are excessively high concerning training results.

Possibly, this performance could be enhanced by increasing the number of training samples. For the validation process assessment of the fault isolation ANN when using measurement sample with noise, the compressor and turbine fault detected error are 18.3% and 8.8% respectively, while the RMS error is 15.3%. The validation process fail rate is high due to the low performance of the training process.

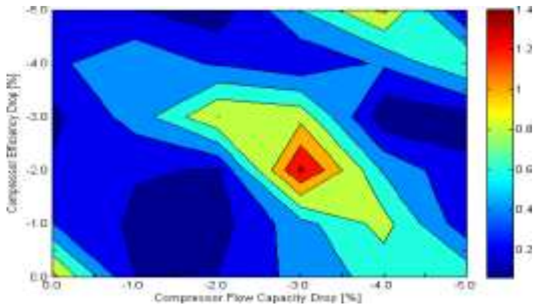

Figure 17: Compressor fault quantification ANN training RMS error (noise).

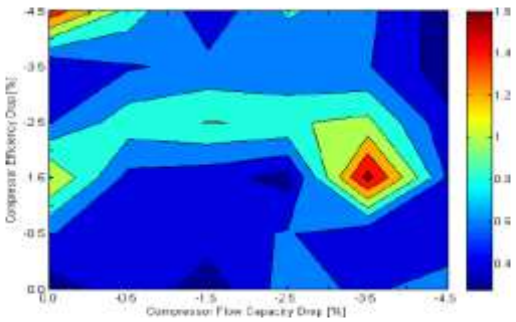

Figure 18: Compressor fault quantification ANN validation RMS error (noise).

From the map of the RMS error as shown in figure 17, the majority of the domain presents RMS error up to 0.6%, meeting the requirements of the diagnostic results. RMS of about 1.4% is presented around the centre domain, which is also acceptable for this kind of analysis. This means the training process of the compressor fault quantification ANN has succeeded. Figure 18 presents the map of RMS error of the validation process of compressor fault quantification ANN when using measurement data with noise. The overall RMS is 0.5%. The centre of the domain presents the highest RMS error around 1.4%, which can be considered acceptable for diagnostic purpose. In addition, the overall behaviour of the training assessment map and the ANN validation map are similar, which means a smooth transition between training points and the validation points, ensuring the same level of accuracy throughout the domain.

Figure 19 is a map of the RMS error of the training process of turbine fault quantification ANN when using measurement data with noise. The majority of the domain presents RMS error up to 0.6%, which is acceptable for engine component fault diagnostic purpose. The right low corner of the domain presents a high RMS error, about 1.6%, the right high corner presents RMS error about 0.8%. They are all acceptable for this kind of analysis. This means the training process of the turbine fault quantification ANN when using measurement data with noise has succeeded.

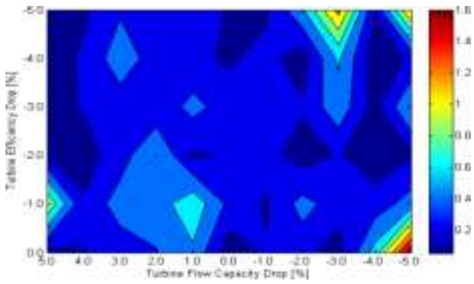

Figure 19: Turbine fault quantification ANN training RMS error (noise).

The RMS map error of the validation process of the turbine fault quantification ANN when using measurement data with noise is shown in figure 20. The right low corner of the domain has an error about 1.5%, which is very close to the one presented by the training process for this region of the map. The centre left side of the domain presents RMS error about 1.0%, with points of 1.3%. The turbine fault quantification ANN can be considered acceptable to perform the turbine component fault diagnostics despite the differences in the accuracy level.

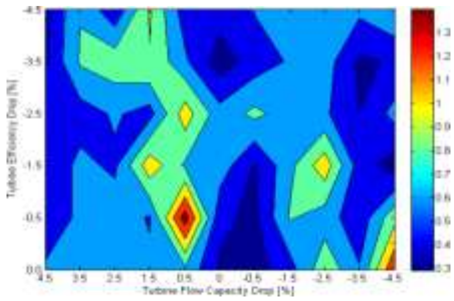

Figure 20: Turbine fault quantification ANN validation RMS error (noise).

In addition, the validation RMS map follows the same behaviour of the training RMS error map, has they both presents their worst performance in the right low corner of the domain, and they both have similar levels of accuracy. The feature indicates that there is a smooth transition between the training points and the validation points, which good ANN behaviour throughout the entire domain. The RMS error level of the ANN when using measurement data with noise is higher than that found for the ANN when using measurement data without noise.

For the combined fault quantification ANN assessment when using measurement data with noise, both training process performance and ANN accuracy have been assessed using the measurement parameter vector as input vector.

15. CONCLUSIONS

The gas turbine diagnostic technique have been applied to an ALSTOM GT11N2 heavy duty engine, which comprises one top-mounted silo combustor, one compressor, and one turbine. The analyses include measurement data without and with noise. Actual data from AFAM phase II, Port Harcourt thermoelectric facility have been used to set up engine model, which was enabled by the application of PYTHIA 2.8 software. The model was adjusted to match the targeted parameters of the reference operational condition that have been used to set up the design point model. The matching procedure yielded error of about 0.08%. Drop in component parameter was applied to the engine model to generate the neural network training and validation samples. The training sample database was also used to study the influence of the independent parameter drop on the behaviour of the engine measurement parameters such as compressor exit temperature and pressure, turbine exit temperature, and shaft power.

However, the nest neural network validation procedure has led to important conclusions. Firstly, the degradation detection ANN has demonstrated excellent performance for both measurements with and without noise. Secondly, the fault isolation ANN has presented good results when analysing measurements with noise, where the results were barely acceptable. In the third case, the compressor and the turbine fault quantification ANNs have presented excellent results concerning measurement without noise, which turned into good results when analysing samples with noise. Lastly, the complete nest neural network structure has presented good accuracy when analysing measurement without noise, but only accepted results could be achieved when using measurement parameter data with noise.

ACKNOWLEDGEMENT

I sincerely wish to appreciate my colleagues in the field of gas turbine for their expertise knowledge contribution to the success of this technical work, especially Jose Biruel Junior. My profound gratitude to my most amiable supervisors Dr Ken Ramsden, Dr I. Y. Li, and Professor P. Pilidis all of the Department of power and propulsion, Cranfield University, United Kingdom, and to my financial sponsor petroleum technology development funds (PTDF) Nigeria. Most importantly to God almighty without whom nothing would have been possible for me.

REFERENCES

1. ESI Africa., "Nigeria: Electricity Generation Improves amid Gas Constraints", *Africa's Power Journal, (*http://www.esi-africa.com/news/nigeria- electricity-generation-improves-amid-gas-constraints/) access May 17, 2017.
2. Gambo, A. S., et al "Electricity Generation and the Present Challenge in the Nigeria Power Sector". *Energy commission of Nigeria, Abuja-Nigeria*. 2010.
3. Urban, L. A., "Parameter Selection for Multiple Fault Diagnostics of Gas Turbine Engines", *Journal of Engineering for Power*, 1975; 225-230.
4. Singh, R., "Managing Gas Turbine Availability, Performance and Life Usage via Advance Diagnostics", *44th Gas Turbine Users Association Annual Conference,* Dubay, UAE. 1999.
5. Li, I. Y., Singh, R., "An Advanced Gas Turbine Gas Path Diagnostics System-PYTHIA", *American Institute of Aeronautics and Astronautics Inc.* 2005.
6. Ogaji, S., "Advanced Gas-Path Fault Diagnostic for Stationary Gas Turbines", *(PhD Thesis), Cranfield University, United Kingdom.* 2003.
7. Li, I. Y., "Gas Turbine Performance and Health Status Estimation using Adaptive Gas Path Analysis", *Journal of Engineering for Gas Turbines and Power*, No. 132. 2010.
8. Lipowky, H., Staudacher, S., Bauer, M., and Schmidt, K., "Application of Bayelsian Forecasting to Change Detection and prognosis of Gas Turbine Performance", *Journal of Engineering for Gas Turbine and Power*, 2010.
9. Bouguet, S., and Leonard, O., "Comparison of Adaptive Filters for Gas Turbine Performance Monitoring", *Journal of Computational and Applied Mathematics,* 2010; 2202-2212.
10. Kurz, R., and Brun, K., "Degradation of Gas Turbine Performance in Natural Gas Service", *Journal of Natural Gas Science and Engineering*, 2009; 95-102.
11. Vodopianov, V. E., "Probabilistic Gas Path Analysis for Gas Turbine engine and its Application", ASME Turbo Expo, 2004; 563-571.
12. McCulloch, W. S., and Pitts, W., "A Logical Calculus of the Ideas Immanent in Nervous Activity", Bulleting of Mathematical Physics, No. 3. 1943.
13. Carling, A., "Introducing Neural Networks", Sigma Press, Wilmslow, United Kingdom,. 1992.

14. Hou, F., "Development of a Neural Network Fault Diagnostics System for Gas Turbine Engine", Cranfield University, 2007.
15. Hertz, J., Krogh, A., and Palmer, R. G., "Introduction to theory of Neural Computation", Addison- Wesley, Redwood City, California, 1991.
16. Palme, T., Fast, M., and Thern, M., "Gas Turbine Sensor Validation Through Classification with Artificial Neural Network", *Applied Energy*, 2011; 88: 3898-3904.
17. Fast, M., Assadi, M., and De, S., "Development and Multi-Utility ANN Model for an Industrial Gas Turbine", Applied Energy, 2009; 86: 9-17.
18. Beale, M. H., Hagan, M. T., and Demuth, H. B., "Matlab Neural Network Toolbox User's guide, Mathworks, 2011.
19. Fast, M., and Palme, T., "Application of Artificial Neural Network to the Condition Monitoring and Diagnostics o a Combined Heat and Power Plant", Energy, 2010; 35: 1114-1120.
20. Ogaji, S. O., Sampath, S., Singh, R., and Probert, S. D., "Parameter Selection for Diagnosing a Gas Turbine's Performance Deterioration", *Applied Energy*, 2002; 73: 25-46.
21. Ogaji, S. O., Singh, R., "Advanced Engine Using Artificial Neural Network", *Applied Soft Computing*, 2003; 3: 259-271.
22. Donat, W., Choi, K., Singh, R., and Pattipati, K., "Data Visualisation, Data Reduction and Classifier fusion for Intelligent Fault Diagnosis in Gas Turbine Engines", Journal of Engineering and Power, 2008; 130.
23. Shivakumar, Pai. S., and Rao, S., "Artificial Neural Network based Prediction of Performance and Emission Characteristics of a Variable Compression Ratio CT Engine using WCO as a Biodiesel at Different Injection Timings", *Applied Energy*, 2011; 2344-2354.
24. ALSTOM., "Gas Turbine Range-Technical Performance", available at http://www.alstom.com/power/fossil/gas/gas- turbines/gt11n2/. 2010.