Reduction of Impacts of Oil and Gas Operations through Intelligent Maintenance Solution

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ABSTRACT

Impacts of oil and gas production operations are always very obvious when there is imbalanced operation, uncontrolled stoppage or catastrophic failure of the system during normal operations. These impacts may range from high flaring and venting of associated petroleum gas, oil release or spillage, equipment damage, fire outbreak to even fatality. Possible causes of imbalanced operations or system failure are categorised into process upset, system degradation, ineffective operation and maintenance procedures and human errors. Effective maintenance strategy integrates major components of the system; people (human factors), operation and maintenance procedures (process) and production plant (technology) to develop an intelligent maintenance solution that is capable of monitoring and detecting fault in the system at incipient stage before operational integrity is compromised. This paper deploys data-based analytics technique to develop condition-based predictive maintenance system to monitor, predict and classify performance of gas processing system. Exhaust gas temperature (EGT) of Gas Turbine Engine (GTE) is one of the operating and control parameters associated with efficiency of the GTE operation. The EGT is measured using several thermocouples, temperature sensors spaced equidistant around the circumference of the exhaust duct of the GTE. Neural network technique of multisensory data fusion is integrated with intelligent maintenance system to monitor performance of GTE, detect fault and classify performance of GTE to optimal, average and abnormal performance.

Keywords

Exhaust gas temperature, gas flaring, Gas turbine engine, incipient fault, intelligent maintenance, multi-class classification, neural network, oil and gas, reliability, thermocouple sensors.

1. INTRODUCTION

Oil and gas release, gas flaring and venting have been observed and accepted as inexorable parts of the processes in all phases of oil and gas production operations; drilling, producing, refining, NGL/LNG extraction and petrochemical products processing. The flared and vented gas, known as associated petroleum gas (APG), which is entrained in crude oil and is released when oil is brought out and processed, has lots of economic values [1].

Oil and Gas production and Processing Plants or systems are close, complex and hierarchically organised systems, bound to decay from stable state (order) to chaotic state, tending to maximum entropy, having stiff operating parameters, resistant to stresses within narrow boundaries and are susceptible to small, unpredicted perturbations [2]. This system's degradation affects systems' performance, reliability and availability, leading to low productivity due to inconsistent operations. It also has serious

impact on the volume of APG flared or vented which in turn leads to environmental degradation. Ineffective maintenance techniques grossly compromise reliability and availability of the production system, which ultimately makes it difficult to optimise asset utilisation in the production facility [3]. According to [4], ''Flaring and venting of associated petroleum gas occurs as a safety measure to safely dispose of gas during emergencies or during the breakdown of machineries''

Maintenance and reliability challenges of oil and gas processing systems seem to negate the envisaged benefits of deployed advanced, innovative technologies and processes, due to inability of the extant maintenance practices to proffer optimal solutions to the problems during operational phase of the systems' life cycle [5].

Condition-based maintenance models have been developed and used in many industrial systems to elucidate maintenance and reliability challenges. Artificial Neural network (ANN) technique of multisensory data fusion is integrated with intelligent maintenance system to monitor performance of GTE, detect fault and classify performance of GTE to optimal, average and abnormal performance.

1.1 Impacts of Reliability and Maintenance Problems in Oil and Gas Systems

In Nigeria, industrial systems maintenance has been a destructive and chronic menace that has plagued oil and gas industries and even the economy of the country at large. The maintenance and reliability challenges are owed to ineffective maintenance techniques that are being practiced in the sector. These practices are very expensive, wasteful and in most cases introduce faults to the systems in the course of maintenance exercise due to human factors.

1.2 30-Day Performance Monitoring of one of the Gas Plants in Nigeria

The NGL extraction/processing plants are set up to gather and process APG from several oil production facilities. One of such plants was designed to process maximum of 650 mscf (million standard cubic feet) of gas per day and produce 25000 – 30000 barrels of NGL per day. The system consists of ten gas turbine driven compressors of which nine were functional during the period of reliability assessment of the plant. Within this period, a total of thirty six unplanned shutdowns were recorded. A greater percentage of these unplanned stoppages was as a result of gas turbine failure due to defective or degraded components. In this system, a progressive decrease in speed of the gas turbine is an indication of present of slow developing fault in the system. It is partly an upshot of gradual decrease in exhaust gas temperature (EGT) of the GTE.

2. Approaches to APG Flaring/Venting Reduction/Elimination

APG gathering for NGL/LNG extraction has really reduced the volume of flared and vented gas, due to deployment of the advanced processing systems, other best practices and procedures. In line with these breakthroughs in the industries, gas flaring and venting could be seen as inevitably breaking of boundary between oil and gas processing system and the ecosystem or physical environment in a "controlled" manner when the safety of the operations are threatened due to unnecessary upset; or uncontrolled manner when there is a catastrophic failure of the processing system due to component degradation or human factor.

2.1 Boundary design of oil/gas production system for Fail-Safe Operations

Understanding the basic operations of oil and gas production systems helps in appreciating the complexity of the system; from exploration, development, production and processing, storage and transportation and marketing. Oil and gas production system comprises people, plant (structural, architectural, control system, safety system), Process (oil/gas, operating procedures, standards and regulatory requirements), environment (local and global communities/ecosystems), and government policies and license requirements. Generally, the assessment of economic viability and technical feasibility to safely extract hydrocarbons is complex including numerous impacting variables that play in stochastically [6].

Hazard of operations, dynamics of the processes and stiffness of operating boundaries make the system dangerous when there is an interaction outside of the designed boundaries of the system, that is, uncontrolled breaking of operating boundaries or designed containment. Effective and optimal control of the system involve monitoring the internal dynamics of the system through its critical parameters or variables (temperature, pressure, liquid levels, flow, vibration, speed, etc.) using sensors and regulating the behaviours or forcing the system's operations to remain within the defined boundaries using actuators or final control elements. Though these systems are always closed and highly pressurised, one of the critical considerations during design phase is 'Fail-Safe Operations. The fail-safe operations ensure the safety of the system, personnel and environment should there be any process upset, component or system failure or any unbalanced operations. Hence, fail-safe operation ensures that operational boundaries are broken safely in a controlled manner whenever there is a system failure.

Typically, gas processing include transporting gas from one vessel to another under pressure in pipelines, by increasing the pressure using compressors; heating and cooling for NGL/LNG extraction, storage and transportation. The success of these operations is achieved if the associated risks are properly managed, reliability of the system sustained and human factors effectively analysed and integrated into the design, operations and maintenance of the system. In view of these, gas processing systems are designed such that whenever safety of the system is compromised, the operating boundaries are safely broken in a controlled manner to avoid catastrophic situation. Boundaries in this context are different valves and actuators that allow, prevent, relieve and regulate gas process variables, when there is need, upset or failure. Theses valves are shutdown valves (SDV), blowdown valves (BDV), pressure safety valves (PSV) and pressure relief valves (PRV). Control valves regulate the internal dynamics of the system, by forcing process variables to remain with designed operating envelops. The diagram below in figure 1 show

simplified schematic and architecture of oil and gas system respectively, indicating some boundary valves.

System failure and ineffective operational procedures have been highlighted as the primary causes of continued venting and flaring in oil and gas industries [7],[8]. According to Allen [9], previous works done in this area of research indicate that both equipment and operational procedures play key roles in sustaining the current volume of APG flared/vented globally.

3. Reduction/Eradication of Gas Flaring Condition-Based Predictive Maintenance

Intelligent maintenance and reliability approach to reduction of impacts of oil and gas operations aim at optimisation of operations and maintenance (O&M) phase of oil and gas system life cycle using advanced engineering tools and methodologies. This is achieved by integrating major components of oil and gas production system; people (human factors), operation and maintenance procedures (process) and oil and gas production plant (technology) to develop intelligent maintenance solution that is capable of monitoring and detecting fault in the system at incipient stage before operational integrity is compromised. Modelling O&M phase of system lifecycle from the perspective of a managed system makes it easier to utilise certain approaches such as system dynamics, agent-based simulation modelling and model-based systems engineering techniques to proffer optimal solution to engineering systems maintenance challenges. From the control system perspective, gas processing system can be analysed, monitored and its operation optimised using sensors information.

3.1 Gas Turbine Engine Performance monitoring

GTEs find their applications both in industrial and aerospace communities. Industrial applications of GTE include driving of high capacity rotary or centrifugal compressors in oil and gas processing plants, generation of electricity while aerospace applications include commercial and military aircrafts. In oil and gas industries, the rotary compressors driven by GTE are used in various applications such as compression of APG for exportation through pipeline, storage, gas injection for reservior maintenance, gas lifting to enhance oil recovery from reservior and for NGL and LNG extraction processes. The power, performance and efficiency of GTE characteristic are the upshots of complex interactions of different subcomponents of gas turbine subsystem and the combustion subsystem [10], [11], [12].

Performance monitoring of GTE considers several pertinent parameters which include ambient temperature, relative humidity, suction pressure, mass flow of fuel gas, quality of fuel gas, quality of inlet air to gas generator, compressor discharge pressure (CDP) of the turbine, firing temperature of the gas turbine, speed of shaft which determines the power output of the GTE [13].

This paper focuses on analysis of exhaust gas temperature data from the GTE system using multisensory data fusion to detect performance degradation at the incipient stage so that planned system stoppage could be scheduled to avoid unbalanced operations which may lead to unnecessary plant shutdown.

3.2 Intelligent Maintenance and Reliability Sustainment

Intelligent maintenance systems utilise plant engineering informatics to monitor the health condition of the system, diagnose the failing components or system and predict the remaining useful life of the system using failure trajectories of the

system. The implementation of these systems requires a combination of human factors, maintenance procedure/process and plant (plant information) in a creative manner. The proposed intelligent maintenance model incorporate key factors of integrated system development life cycle (SDLC) into maintenance reliability improvement procedure during operations and maintenance phase of the system life cycle as indicated in Figure 5.

3.3 Condition-based Predictive Maintenance: An Intelligent Maintenance Solution

Condition-based predictive maintenance (CBPM) approach is an intelligent maintenance (IM) philosophy that monitors the production system's conditions and performances using sensor signals, detect fault at the incipient stage, estimate and predict the future state of the system. In addition to deployment of advanced engineering tools and techniques to modelling and development of intelligent maintenance solution, it also advocates incorporation of the maintenance system in the product life cycle. Thus CBPM is a holistic approach to enterprise asset lifecycle optimisation and management.

3.4 Related Works on Intelligent Maintenance System

A review of past research works on intelligent maintenance system shows that it has been on since year 1998 and in progress with various names such as intelligent maintenance system [14], intelligent prognostic system [15], e-maintenance [16], condition monitoring system [17], condition-based maintenance, predictive maintenance system [18]. These maintenance systems are mostly developed for specific assignments; they are not scalable, portable or applicable to other systems [15]. For instance, commendable successes have been recorded in intelligent maintenance system for commercial and military aircrafts, marine vessels and industrial machinery health condition monitoring and prognostics using advanced engineering principles such as multi-sensor data fusion (MSDF) technology [14], [16], [18]. Bayesian techniques have been used to develop diagnostic model for fault detection and condition based maintenance of offshore wind components [19]. In [20] Bayesian updating method was adopted to monitor degradation of bearings conditions in order to detect incipient fault and predict residual life of the bearing. Bayesian probabilistic model and naïve Bayes classifier have been implemented by [21], [22] for bearing condition monitoring and fault detection. Cascade correlation neural network classifier was found effective for vehicles door system degradation and failure detection [23].

4. Multisensory Data Fusion for Intelligent Maintenance system

Applications of multisensory data fusion (MSDF) technology span a wide range; from robotics, automated manufacturing, remote sensing and condition-based maintenance of industrial systems to military applications such as battlefield surveillance, tactical situation assessment and threat assessment. For a drivetrain and high capacity industrial gas compressor applications, for example, sensor data can be obtained from accelerometers, temperature sensors, pressure sensors, flow sensors, and vibration sensors. An online condition-monitoring system combines these observations in order to identify signs of failure, such as abnormal gear wear, shaft misalignment, bearing failure and low performance of the system. The use of such condition-based monitoring is expected to reduce maintenance costs, reduce operational risk and improve safety, improve productivity and reliability [17]. MSDF techniques can be categorised into probabilistic and statistical methods, Least-square and mean square methods and heuristic Methods. The heuristic methods include artificial neural network (ANN), fuzzy logic and approximate reasoning. In this paper, ANN technique of MSDF for GTE system performance classification is presented.

4.1 Basic Estimation Fusion Process

Consider a system with n number of sensors, at the sensor node, the following parameters are specified: $\mathbf{Z_i}$ is the observations with, $\mathbf{R_i}$ the covariance matrix of the associated noises

x is the variable to be estimated, and
$\hat{x}$ is the local estimate of x, with its covariance matrix $\mathbf{P_i} = \mathbf{cov}(\hat{x})$
Thus the estimation error $\tilde{x} = \hat{x} - x$
For unified fusion model:

$$\mathbf{z_i} = \mathbf{h_i x} + \mathbf{\eta_i} \qquad (1)$$

Where: $\mathbf{z_i}$ is the measurement of the ith sensor and $\mathbf{\eta_i}$ is the measurement noise

A local estimate is considered as an observation of the estimate and is given by:

$$\tilde{x} = x + (\hat{x} - x) \qquad (2)$$
If the new observation $\hat{x}$ is actually the estimate of x, the standard distributed fusion model is given as:
$$\tilde{x} = x + (- x) \qquad (3)$$

Artificial neural network technique of multisensory data fusion for estimation, prediction and classification is very effective due to its supervised learning capability, its strengths and efficiencies include [24], [25], [26];

- Computation on each node of ANN is done concurrently independent of each other.
- ANNs gather knowledge through inspection of the training dataset, makes intelligent predictions on the data and based on this acquired knowledge is able to produce desirable output on new dataset (test dataset).
- With its adaptive capability, they can adjust their weights matrix to efficiently achieve a given task. ANN system adapts by iteratively adjusting the weights in order to improve subsequent results.
- ANN systems are universally considered as approximators with appreciable accuracy.
- ANN systems are non-linear models capable of modelling any complex non-linear relationships.
- ANN models are robust to noise, resilient and fault tolerant

A comprehensive review of neural network classification applications can be found in [27].

4.2 GTE performance classification for incipient fault detection

The presence of multiple faults in a system with many interacting variables such as GTE system can make fault identification very complex, especially at the incipient stage of a slow developing or evolving fault. The introduction of ANN that mimics the ability of a biological neuron in the human brains to learn and adapt the changing environment provides an intelligent solution, especially when there is no availability of exact physic-based mathematical

models of the GTE system [28],[29]. Several methods have been used over the years to solve classification problems; these include statistical classification techniques, Bayesian classification approaches [21], [22], linear classifiers, nearest neighbourhood classifier, support vector machine and neural network based classification techniques.

Classification in machine learning is the problem of identifying similar attributes among many entities in a given set of data and categorising them into classes [30]. Classification process is viewed as a supervised learning with a training set of properly identified observation

Neural network classification techniques include linear perceptron classifier, radial basic network classifier, recurrent network classifier, cascade correlation neural network classifier [23], feedforward neural network classifier and learning vector quantisation network structure [31]. MLP FFNN Classification of GTE System EGT

The ANN adopted in this study is a multi-input-multi-output (MIMO) system developed to monitor and classify GTE system performance in oil and gas processing plant.

In Feed forward MLP neural network classifier, the input vector is fed into the input layer of the network, each input unit j, produces output V_j, which is equal to the input value I_j. The output V_j is then fed forward to the hidden layer through weighted connections where activation functions determine the final output of the network through output layer. One of the popular activation functions for back propagation network is sigmoidal function S_c : $R \rightarrow (0,1)$ defined by:

$$S_c(x) = \frac{1}{1+e^{-cx}} \tag{4}$$

The constant c can be selected arbitrarily and its reciprocal $1/c$ is called temperature parameter in stochastic ANNs. The value of c affects the shape of the sigmoid function. That is, as $c \rightarrow \infty$, the sigmoid converges to a step function at the origin. For simplicity sake, c is usually set at unity (1).

Let $X = (x_1, x_2, \ldots, x_i)$, be a set of normalised input vector in n-dimensional space which are to be classified into k different classes, for multi-class classification problem, $k \geq 3$. The output vector X in n-dimensional input space and a unit j in hidden or output layer, the net input I_j to unit j is given by:

$$I_j = b_j + \sum_{i=1}^{n} W_{ij}\ V_i \tag{5}$$

Where W_{ij} is the connection weight from the unit i in the previous layer to unit j in the next layer
V_i is the output of unit i from the previous layer
b_j is the bias of the unit.
With the net input I_j to unit j, using sigmoidal function, the output V_i is given by:

$$V_i = \frac{1}{1+e^{-I_j}} \tag{6}$$

The parameters of neural network are estimated by minimising the error, that is, the difference between the actual output A_j and the predicted output V_j. This error is known as the cost function; it signifies the accuracy of the classifier. Mean square error is the mostly used cost function and is given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - V_i)^2 \tag{7}$$

4.3 Multi-Class Classification of GTE Performance Using MLP FFNN

Multi-class performance classification of GTE is a problem of building a system that accurately maps an input feature space to

output space of three or more classes [32]. Multi-class classification has been used for object classification [33], speech tagging and recognition [34], [35], text categorisation and information retrieval [36]. Figure 3. Shows a architecture of multi-class neural network model for GTE system performance classification.

A multi-class, also known as K-class, neural network classification problem can be expressed as; for n-dimensional feature space hθ, and a training dataset X_{tr} C h_θ, where each element x in X_{tr} is associated with class label C, C ϵ Class Labels = {C^1, C^2… C^k}, k ≥ 3.

A neural network Ƒ can be trained on X_{tr} such that given a set of feature vector x ϵ X, Ƒ(x) ϵ Class Labels. Ƒ is a neural network whose weights are computed by a neural learning algorithm.

For a given neural network, the input and output at a hidden node j, is given by:

$$I_j^h = \sum_{i=1}^{N} w_{ij}^h x_i \tag{8}$$

$$Z_i = g^h(I_j^h),\ \ j = 1, \ldots, H \tag{9}$$

Where x_i is the input of the feature vector X, w_{ij}^h is the weight association with input x_i to the ith hidden node, H is the number of the hidden node, $g^h(\bullet)$ is the activation function used in the hidden layer.

In the output layer, each node V_k has the input and output as:

$$I_k^o = \sum_{i=1}^{N} w_{ij}^o z_j \tag{10}$$

$$y_k = g^o(I_k^o),\ \ k = 1, \ldots, M \tag{11}$$

where z_j = output value from the jth hidden unit,

w_{kj}^o = weight associated with j^{th} hidden node and the kth output nodes

$g^o()$ = the activation function used in the output layer which is the sigmoidal function.

5. Case Study System

The focus of this paper is on gas processing system which involves compression, heating, cooling and separation of various hydrocarbon components. The system is made up of trains of high capacity gas compressors, driven by gas turbine engines (GTE). The GTEs are the pivot of these operations because they drive the gas compressors and their exhaust gas is used as heating medium for NGL or LNG extraction processes.

A single train of gas compression system comprises of gas generator (GG), combustion chamber (CC), GT, power turbine (PT) with associated gear box and gas compressor (mostly rotary or centrifugal compressor). The interactions of the components and their associated parameters give rise to power, performance, efficiency and characteristics of the GTE system. The diagram in Figure 4 highlights components level, parameters and functional interactions within gas processing system.

In this paper, performance of the GTE system is analysed and classified using EGT sensor data for incipient fault detection. Seventeen thermocouple temperature sensors are used to monitor exhaust gas temperature of the GTE, one of the critical parameters of system which affects many system variables and is affected by other variables as well. For example, temperature and mass flow of the exhaust determine the speed of the power turbine that drives the rotary compressors which in turn compress the process gas. As the load of the driven compressors increases, the fuel flow increases, leading to increase in firing temperature of the gas turbine [37]. The speed of the compressor, gas turbine, power turbine and the firing temperature depend on the fuel flow and

quality of fuel (constituents of fuel, wet/dirty fuel) and compressor discharge pressure of the GG. Sensor data from this system was collected periodically over a period of thirty days with two hundred and fifty data instances. The seventeen thermocouple sensors are the seventeen input features and three classes as target outputs, making the data size of 3000 (150 by 20 matrix). The data was pre-processed and normalised using z–score and min-max normalisation techniques. FFNN with back propagation model was used to predict and classify the performance of GTE system using exhaust gas temperature data, with seventeen sensor data set as inputs to the model and the target output as classes of health state or performance condition of the system. The decision table below in table 1 indicates EGT ranges for a given performance and their class labels.

Given a training dataset $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), …, (x^{(m)}, y^{(m)})\}$
Let L = total number of layers in the network
S_L = number of unit (excluding bias unit) in layer l
In this analysis, L = 3 (that is, input layer, one hidden layer and output layer).
S_1 = 17 neurons in input layer
S_2 = (8, 9, 10, 11, 12, 14, 15), number of neurons in hidden layer for different runs of the experiment.
S_3 = 3 neurons in output layer
$y \in R^k; \ k \geq 3$

$C^1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$ Optimal performance of GTE

$C^2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$ Average performance of GTE

$C^3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ Abnormal performance of GTE

6. Results of the GTE Performance analysis

The classification results shows that S_2 = 7, 9 and 10 give accurate classification results as indicated in figure 5; meaning that the multiclass neural network can be used to monitor the performance of the GTE using the EGT sensor data. Poor classification accuracy is achieved when the number of neurons in the hidden layer S_2 is 13. The Essence of performance monitoring of GTE system is to detect the start of average performance of the system so the operations of the gas processing plant can be properly managed without unnecessary system upset or stoppage. This decisional information if communicated on time could be used to reduce impact of oil and gas operations such as uncontrolled venting and flaring, oil release or spill, in extreme case fire outbreak which may impact on the business, environment or may lead to fatality.
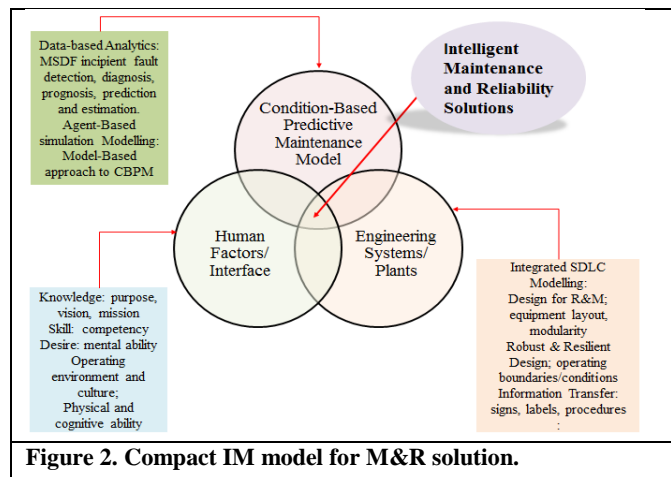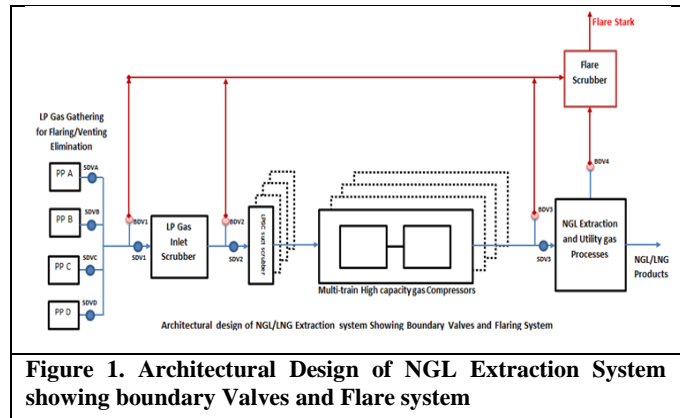
7. Conclusions and Future Works

This paper has provided intelligent maintenance solution through integration of condition-based predictive maintenance strategy into integrated oil and gas processing system development life cycle. The reliability and maintenance challenges in oil and gas have grossly affected normal operations of the system, which in turn leads to serious safety, health, business and environmental impacts. Reduction of impacts of oil and gas operations can be achieved by properly monitoring performance of the system for incipient fault detection.

Total performance condition monitoring of oil and gas processing system can play a major role in providing early warning of potential failure and performance deterioration of the system. One

of the key operating and control parameters associated with performance efficiency of the GTE system operations is the EGT. In this paper, MLP FFNN multi-class classification technique was used to monitor and classify performance of GTE system which drives rotary compressors for NGL extraction. Performance classification of the system was carried out on EGT data from seventeen thermocouple temperature sensors. The GTE system performance was classified into optimal performance (EGT range of 1275 - 1426ºF: C^1); average performance (EGT range of 1175 - 1270ºF: C^2); abnormal performance (EGT range of 1075 - 1170ºF: C^3). The classification accuracy was high (100% correct classification) when the number of neurons in the hidden layer of the model were S_2 = 7, 9 and 10. S_2 = 13 gave relatively poor classification result. This information is very useful for effective operation and maintenance management of the system.

This research categorises oil and gas system data into monitoring, performance and condition datasets. In the course of the research project, condition dataset such as vibration data and bearing temperature shall be analysed for fault detection estimation and prediction using wavelet packet, Hidden Markov and Bayesian classification techniques
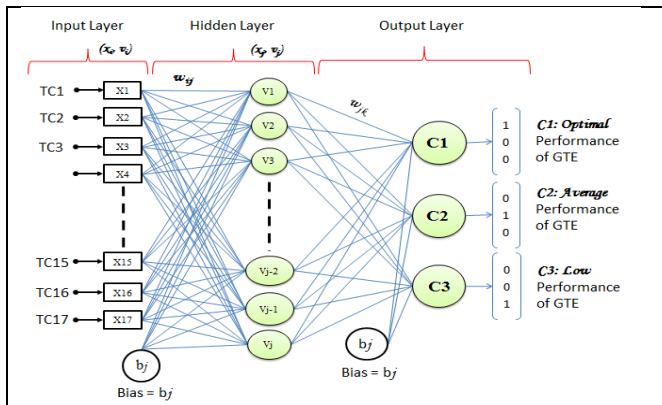
8. Figures and Tables

Figure 1. Architectural Design of NGL Extraction System showing boundary Valves and Flare system

Figure 2. Compact IM model for M&R solution.

Figure 3. Architecture of multi-class neural network model for GTE performance classification
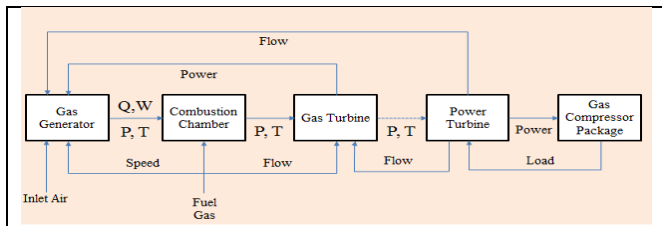

Figure 4: Components and Functional Interactions within gas processing system

Table 1. Decision table showing EGT ranges and GTE performance class labels			
EGT Range	GTE Performance	Class Label	Required Actions
1275 - 1426ºF	Optimal Performance	1	No action
1175 - 1270ºF	Average Performance	2	Plan for inspection; incipient fault
1075 - 1170ºF	Abnormal Performance	3	Needs urgent maintenance actions

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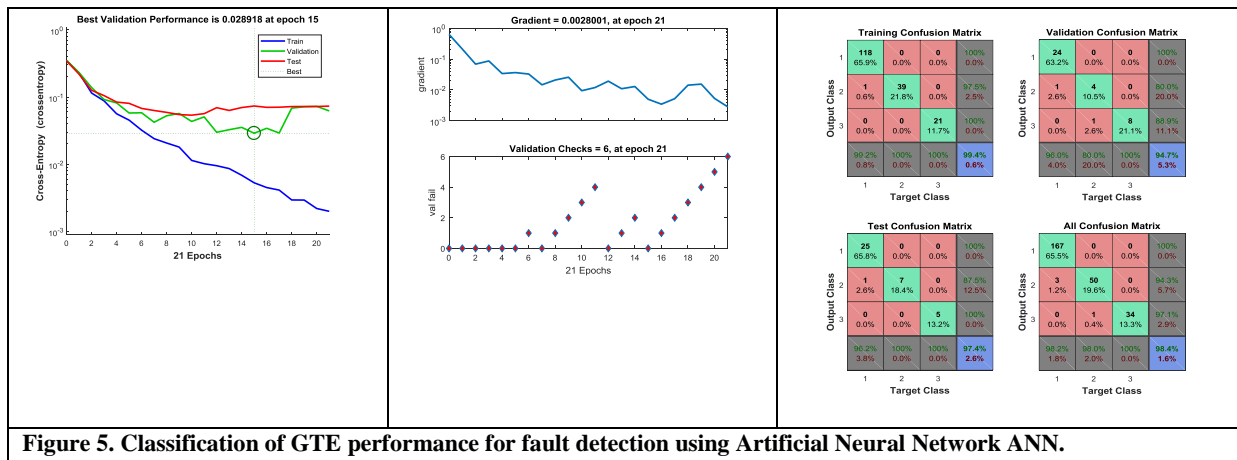
Figure 5. Classification of GTE performance for fault detection using Artificial Neural Network ANN.