Performance Based Anomaly Detection Analysis of a Gas Turbine Engine by Artificial Neural Network Approach

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ABSTRACT

This present work follows our earlier research efforts on fault diagnosis and prognosis solutions considering statistical and physics based approaches. In-service performance analysis and detection of any malfunctioning in an operating small sized gas turbine engine using artificial neural network approach is the central theme of this work. The measured engine operating and performance parameters are used to train two neural network models, namely back propagation and generalized regression. Following the training and validation of the neural network model, simulation results for test data corresponding to various engine usage stages are found to be close by two models. The analysis identifies an anamoly in the simulated and measured data collected 17 months after the engine overhauling which may be attributed to deliberate adjustments in the operating parameters. A threshold for anomaly detection in terms of the probability levels for variation of the rated power capacity of the engine is also studied.

1. INTRODUCTION

Gas turbine (GT) configurations typically include single or multi-shafts, closed loop, simple or combined cycle, combined heat and power etc. and is typically used to generate electrical power. In spite of wide variations in the design, complexity, applications, operating conditions etc. the failure mechanisms are generally experienced to be identical. The GT life limiting issues of concern are low cycle fatigue (LCF), high cycle fatigue (HCF), creep, oxidation, corrosion, foreign object damage, etc. For effective and efficient engine health monitoring (EHM), a host of parameters are usually monitored in modern GT that include speed, power, gas inlet pressure and temperature, exhaust and operating pressure and temperature, gearbox, journal and thrust bearing vibration and temperature (Clifton, 2006; Hoeft et. al., 2003).

On-line condition based monitoring of plant operation is extremely important for plant safety, reliability and availability and maximization of the power output and lowering life cycle costs. In recent years, with the rapid development of condition monitoring and forecasting, information processing, fault detection and artificial intelligence technology, it has been possible and feasible to monitor and forecast equipment condition and assess its health in real-time. It is well recognized that optimized maintenance practices within an industrial setting require the correct blend of condition based maintenance (CBM) strategies. (Hoeft et. al, 2003; Sobanska & Szczepaniak, 2006, Fast, 2010).

With usage, the health of the GT components deteriorates and affects the performance of the engine. The continuous degradation in performance and its rate plays a crucial role in establishing the time intervals between major overhaul (Clifton, 2006; Fast, 2010; Fast & Palme, 2010). The sophisticated technologies being incorporated into new gas turbines allow operations at higher pressures and temperatures with higher efficiencies. The trend of preventive maintenance at regular intervals is being replaced by CBM techniques to further reduce the maintenance costs. This makes intelligent and robust engine health and performance monitoring techniques that are sensitive to changes in the engine condition important for higher safety, reliability and availability of the units (Angeli & Chatzinikolaou, 2004). The capability to detect impending faults from the current engine conditions and issue early warning with minimum false positive is also desirable.

The malfunctioning in a GT can occur from component physical damage, changes in operational control and settings, faults in data monitoring devices, calibration etc. Some of the faults will unavoidably occur in an engine due to wear and/or malfunction of some components affecting system performance, as well as their combinations. Some of the malfunctioning can be rectified by taking appropriate corrective actions and requires fault diagnosis solution. Due to the associated complexity, evolutionary Artificial Intelligence techniques (Russel & Norvig, 1995) are being increasingly applied for diagnosis in GT.

Our current research attempts to investigate the feasibility of developing performance based GT-EHM system using operating data driven artificial neural network (ANN) modeling and techniques. The ANN models are developed such that it can represent the basic working of a freshly rebuilt GT and predict the critical performance metrics like the output power or the driven unit load. Anomaly detection is performed by comparing the predicted behavior of the freshly rebuilt GT obtained through trained ANN, with the actual measurements during the operation. The work related to the ANN as reported here follows our earlier research activities on diagnostic and prognostics solutions using statistical and physics based approach (Saxena, et.al., 2011; Kumar et.al., 2011). This work using ANN approach is our first attempt to look for an alternative solution for anomaly detection.

2. ANN FOR ANOMALY DETECTION

Anomaly detection methods are traditionally based on limit value checking of key measurable parameters without simulating the human reasoning activity. Numerous methods of anomaly detection leading to fault diagnostics have been developed and applied effectively to identify the machine/engine faults at an early stage using different performance parameters such as current, voltage, speed, temperature, and vibrations (Russel & Norvig, 1995; Zhu, 2009; Kumara et.al., 2012). A brief discussion is made in this section on ANN approach for anomaly detection. In the case of very complex time-varying and non-linear systems, where reliable measurements are very complicated and valid mathematical models do not exist, a number of different methods have been proposed by researchers. These methods come from the area of Artificial Intelligence and allow the development of new approaches to anomaly detection in dynamic systems like the GT.

Briefly, artificial neural networks (ANN) are massively parallel-interconnected networks that have the ability to perform pattern recognition, classification and prediction. A wide variety of engineering problems can be solved using ANN which is especially useful in situations where the data volumes are large and the relationships among variables are unclear or hidden. The network is trained to learn from the examples and forms an internal representation of the problem (Russel & Norvig, 1995). For anomaly detection, it is needed to relate the measurement data to the ideal performance, and distinguish between normal and abnormal states. Input vectors are introduced to the network and the weights of the connections are adjusted to achieve specific goals. An adaptive algorithm automatically adjusts the inputs weightage to minimize the mean square of the error between the actual output value and the desired target value. A significant feature of neural networks is that an approximate model may be adequate to internally map the functional relations that represent the process. A recent work classified between normal and abnormal vibration data for a large turbine (210 MW) in a power plant using artificial neural networks (ANN). Self-organization map is trained with the normal data and simulated with abnormal condition data from a test rig (Patel & Prajapati, 2011; Samhouri et. al., 2009). Different unbalanced conditions are introduced on test rig at laboratory and vibration data is collected to simulate the network.

The choice of network architecture is dependent on the problem. Classification, linear or non-linear problems, with or without underlying system dynamics guides the choices of network composition and the topology. A single feedforward network describes a simple mapping network that can be used in classification or for mapping of simple input output functionality. It is defined through a single layer of neurons (Fast, 2010; Russel & Norvig, 1995). Hence, the knowledge storage capacity is restricted and only simple logic relations can be mapped. An extension of this is the multi-layer feedforward network, also found as multi-layer perceptron (MLP). This network architecture is defined through a minimum of one hidden layer of neurons. The number of hidden layers can be increased depending on the problem. However, a MLP with three hidden layers is sufficient to map every continuous function by adding a certain number of neurons to meet required complexity (Riad et.al, 2010; Sprecht, 1991; Kaminski, 2010).

2.1. Model Selection

Back propagation (BP) algorithm is a steepest descent algorithm, in which the performance index is the mean square error (Russel & Norvig, 1995; Fast & Palme, 2010). It can be used to train multilayer neural networks. Based on the previous experience, a three-layer BP network, with tan-sigmoid activation function in the hidden layer and linear activation function in the output layer has been considered in this work. The training and simulation work is performed using MATLABTM and utilizing its NN toolbox functions. As observed by many researchers, the BP model can approximate virtually any function to any degree of accuracy, provided sufficient hidden units and training sets are available. The learning rate and the momentum are two important parameters for training the network successfully. Levenberg-Marquardt (LM) algorithm has been used for network training, validation and testing as it finds the best weights by minimizing the function. The ANN model consists of three layers of units: a layer of inputs is connected to a layer of hidden units, which is connected to a layer of output units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. Due to the availability of a large number of training data, the number of neurons in the hidden layer is considered as 20 and 10 and validation of the model is done with 20 percent of the input data. In order to check the consistency of results, a generalized regression neural network (GRNN) modeling is also implemented. However, the input-output variables are kept the same as with the back propagation neural network (BPNN).

For most engineering problems, it is difficult to know beforehand how large and complex a neural network should be for a specific application. Besides the input-output variables, the optimum number of hidden units depends on several other factors, like number of training cases, noise in the targets, complexity of the function or classification, network architecture, type of activation function, training algorithm, and regularization. A decent performance of a ANN model may be obtained by setting the number of hidden layers equals one as more hidden layers are generally harder to train. Secondly, the thumb rules available only relate the number of neurons (N) in hidden layer with size of inputs and output variables, ignoring other factors. (Berry & Linoff, 1997, Boger & Guterman, 1997). These rules are generic and provide only a starting guide. Ultimately, the selection of architecture for neural network analysis will come down to trial and error. Furthermore, a rough approximation can also be obtained by the geometric pyramid rule. For the simple three layer network as considered in our work, the number of neurons in hidden layer was first set at square root of m x n with n input and m output neurons, then increasing the number of nodes to achieve best fit. Most of the engineering analysis suffers from limited available data for analysis, thus restricting to small number of neurons in the hidden layer as offered by thumb rules and pyramidal rule. The risk of over-fitting tends to be more in such situations. Over fitting makes the network learn well from training data set, but performs poorly for test data set. In the present work, number of nodes in hidden layers is chosen by trial and error starting from the small number of 5. Under fitting occurs when there are too few neurons in the hidden layers to adequately detect the signals in a complicated data set. Considering all these aspects and availability of large 459 training data set in our work, several trials found the optimum node size to be 20 in the hidden layer with minimum error. This decision is also supported by the default neuron number of 20 adopted in MatlabTM NN toolbox functions, namely nntool and nftool. Larger numbers of neurons adopted here than estimated by thumb rule in the hidden layer give the network more flexibility because the network has more parameters it can optimize. Besides, 10 neurons in a few cases were also considered for comparison of results. A few recent works considered similar number of nodes for vibration based ANN analysis while training was implemented using Matlab toolbox (Samhouri et. al, 2009; Massad, 2009).

2.2. Variable Selection and Data Acquisition

Variable selection and data acquisition are the two key elements for successful modeling of systems behavior and analysis. In ANN approach, the training data is crucial for creating a good generalization of network covering a broad range of the systems behavior. Maintenance and operational data from a small size GT engine was collected over three years for a large number of operating and maintenance parameters. However, for the current work, eight of these parameters are used for training and validation of the ANN model as well as testing and simulations. The selections of the input and output variables of the ANN have been made based on the physical significance, working and thermodynamic principles of the gas turbine operation. Four input variables selected are the gas pressure, two fuel control valve angles and air inlet temperature, while the four output variables selected are the speed, load, exhaust and operating temperatures. This approach has been based on performance monitoring guidelines prescribed by a typical turbine OEM (Hoeft et. al., 2003). Figures 1 and 2 show the typical data profile for the four input and output variables for the GT, respectively. The measured data has been scaled with respect to their mean value as shown in the figures.

3. MODEL TRAINING AND VALIDATION

As mentioned earlier, LM algorithm is used for the back propagation neural network (BPNN) training and model validation and results are displayed in Figures 3 and 4 for a four input-one output and four input-four output BPNN model, respectively. The training data was selected from measurements from the freshly rebuilt turbine operation immediately after a major overhaul and over the duration of the first three months of steady state operation. In the absence of any system model and reference data, it is assumed that this performance data would represent the healthy state of the turbine. In Figure 3, it is observed that the four input-one output BPNN model training yields very consistent and converging results. The output considered for this plot is the power or the driven unit load.

When compared with Figure 4, it is evident that the number of epochs required to reach the goal during training for the four input-four output BPNN model is much higher than that required for the four inputs-one output BPNN. It is possibly because of the numerically redundant input parameter of VGV angle (Figure 1) and the output speed

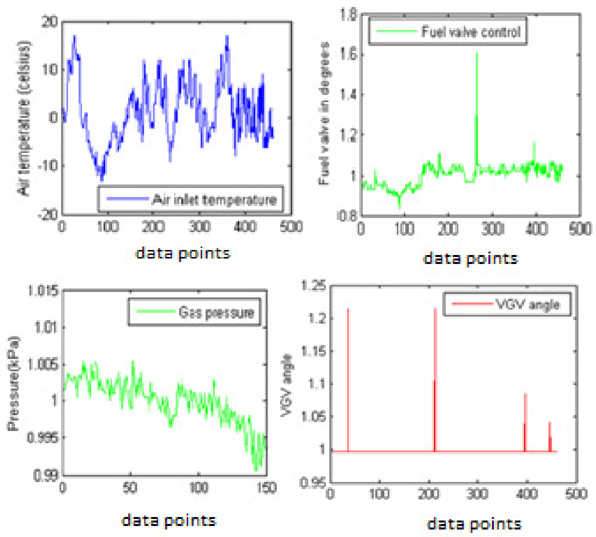

Figure 1: Typical data profile of four Input parameters, Air inlet temperature, FV Angle, Gas pressure and VGV Angle (data scaled)

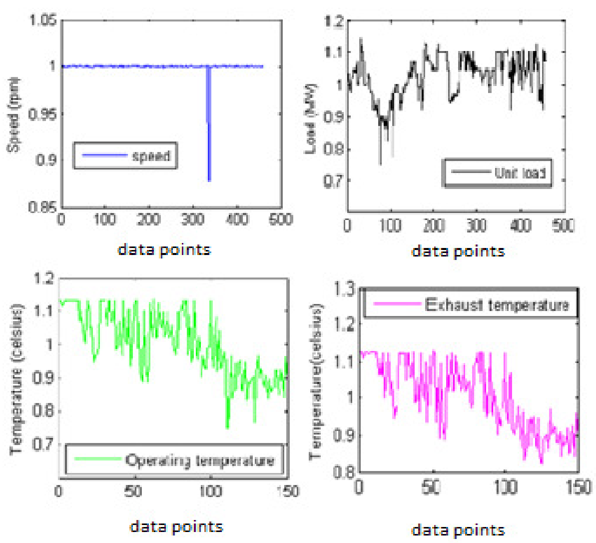

Figure 2: Typical data profile of four Output parameters, namely load, speed, exhaust and operating temperatures (data scaled)

(Figure 2), that are usually very consistent for industrial gas turbines working under steady state conditions. This suggests that the four input-four output model is not suitable for the current set of training data and model selection.

3.1. Generalized Regression Model

The present work is extended to general regression neural network (GRNN) model in view of its fast learning and optimal regression convergence abilities avoiding iterative procedures. The BPNN model needs a large number of iterations to converge to the desired solution. GRNN is similar to probabilistic neural network (PNN) is an

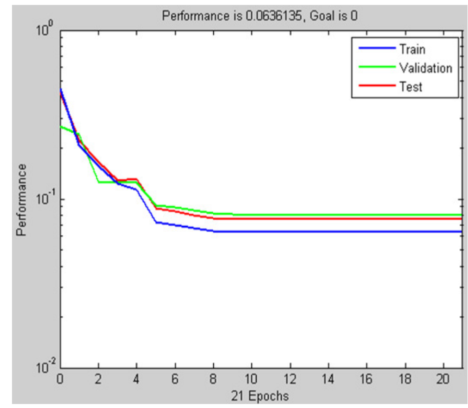

Figure 3: Training of the four input - one output (unit load) BPNN with Levenberg-Marquardt algorithm

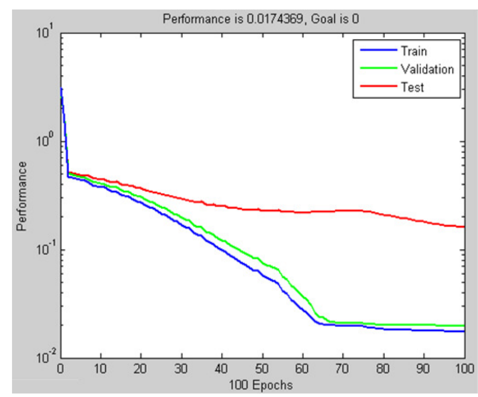

Figure 4: Training of the four input - four output BPNN with Levenberg-Marquardt algorithm

alternative solution when adequate training data are not available in real-time situations. This makes GRNN a very useful tool to perform predictions and comparisons of system performance in practice. It can be used for prediction, modeling, mapping, and interpolating or as a controller (Sprecht, 1991; Russel & Norvig, 1995; Kaminski, 2010).

Figure 5 shows the comparison of the measured data (target) and simulation results (output) obtained using the GRNN during its training with a four input-one output model while predicting the used data set. The figure suggests that the GRNN model may not be predicting like the BPNN model. This can be attributed to the choice of the NN model architecture and the values of the input and output parameters. The figure shows good correlation between the target and output suggesting the effective training of the GRNN model with the unit load output.

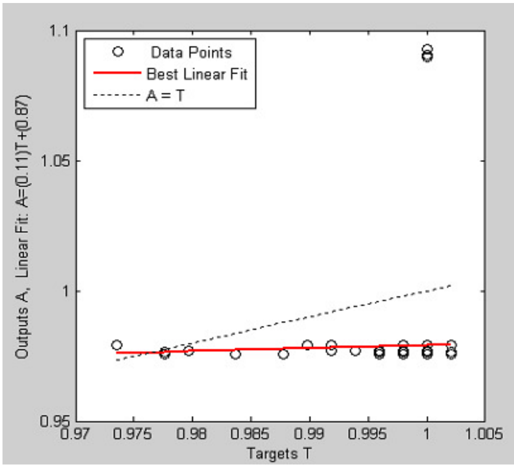

Figure 5: Comparison of measured data and simulation results using GRNN model using training data set with four inputs and one output model

4. SIMULATION

The simulation of the engine performance parameters was done using the trained four input-one output BPNN as well as GRNN models. The different data sets used for the simulation are given below:

- **begin:** This corresponds to a group of 100 data points collected at the 3rd month since overhauling at the beginning of the operation period and represents a freshly rebuilt engine state as the data is close to the training set.
- **intermediate:** This corresponds to a group of 154 data points collected between the 17th-18th month of steady operation of the turbine and represents the 'intermediate' engine state as the data corresponds to the half-way to the end of the operation period.
- **end:** This corresponds to a group of 179 data points collected between 35-36th months of steady state operation and represents the 'used' engine state as the data is close to the end of the turbine design life cycle prescribed by the OEM.

The training data, as discussed earlier corresponds to the operating data during the first three months of operation and represents the performance of a freshly rebuilt system. The aim of the simulation study was to predict the engine performance for a freshly rebuilt engine, and compare it with the measured data to detect any anomaly and inconsistent behavior of the engine performance. The simulation output and the observed target data using BPNN and GRNN models are compared as displayed in Figures 6 and 7, respectively.

In Figure 6, it can be observed that the scatter in the plots (for the 'begin' and 'end' data sets) increases with usage. This is due to the fact that the trained BPNN model predicts the unit load for a freshly rebuilt engine. With usage the performance of the engine degrades, and the measured performance index in terms of the unit load starts deviating from this bench line level simulated by the trained BPNN. However the maximum spread is observed for the 'intermediate' data which may suggest potential anomaly.

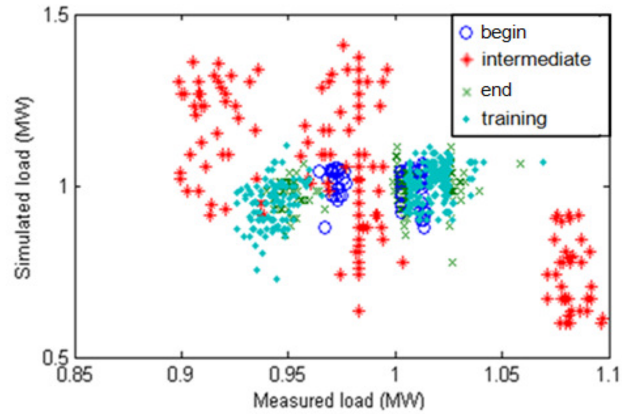

Figure 6: Comparison of the simulated and measured load (scaled) data for different data sets using BPNN model

In Figure 7, a similar trend is observed in the means of the simulated load for different test data sets using the GRNN model. This suggests the possible applicability of both BPNN and GRNN models for engine performance. Also, reducing the number of hidden neurons to 10 does not change the test data mean significantly. Consistently, the simulation results for the 10 neuron hidden layer exhibits a marginally lower value than those obtained with 20 neurons. The mean of the intermediate data is observed to be much lower than the other data sets and will be discussed later. In Figure 8, the comparison of the simulated and simulated data points using the trained BPNN for the 'end' data set is shown. The low correlation reiterates the observation that the deviation between the simulated and measured unit load is high for the 'end' data set.

Under idealistic situations, the simulated and target data points, respectively A and T, and so the linear fit and A=T line should all lie very close. However, for realistic situations, analysis shows that the data points in all cases fit linearly with high correlation coefficients (over 0.90) as typically shown in Figs. 5 and 8. This confirms the modeling - simulation output (A) is consistent with target data (T) as desired. Mismatch between the linear fit and A=T line are also observed and can be explained by the difference in the scattering nature of A and T data. Fig. 8 shows the simulation results have restricted and suppressed scatter band (0.95 to 1.05) when the scaled target load varies over 0.78 to 1.14. In other words, the simulation results seem to be somewhat conservative as compared to target data and tend to lie closely around the mean. This point needs to be examined further at a later stage with more trials and errors with network structure.

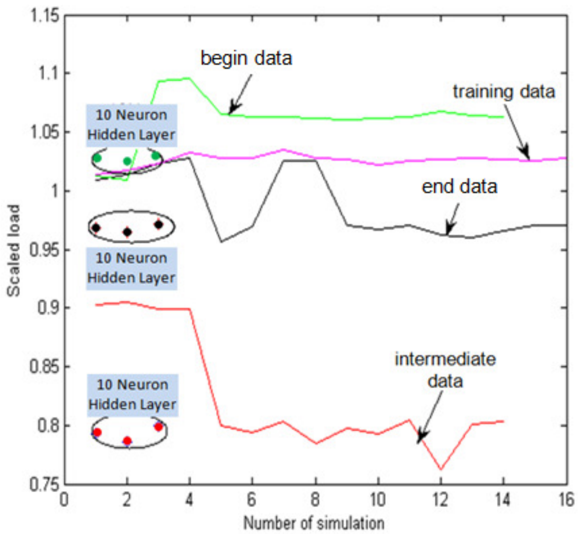

Figure 7: Simulation results for load demonstrating the variations for mean values for different data set using GRNN model

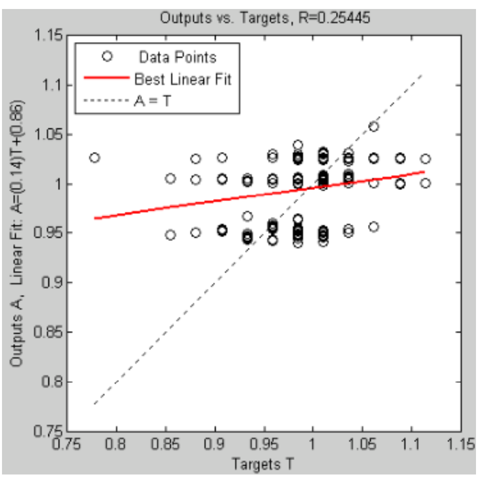

Figure 8: Network simulation output and target data (both scaled) for the 'end' data set with four inputs and load output BPNN model

5. RESULTS AND DISCUSSION

Discussion on the qualitative and quantitative analysis of results is made here in the light of engine performance based anomaly detection in the gas turbine using BPNN and GRNN models. The training of the four input-one output BPNN model with 459 data points, resulted in fast and adequate numerical convergence, as shown in Figure 3. However, attempts to train the four input–four output BPNN model using the same training data set did not yield similar satisfactory training performance (Figure 4). When tested after training, two of the four output parameters, namely load and EGT yielded better result compared to the speed and operating temperature. Hence, a four input-one output GRNN model was trained to predict the unit load for further testing and simulation.

The unit load was simulated using the trained BPNN and GRNN models for different test cases represented by 'begin', 'intermediate' and 'end' engine condition, as displayed in Figure 6 and 7, respectively. The Figure 5 shows that the scatter between the simulated and measured data points is increasing steadily with the usage. This is because the trained BPNN models are simulated the engine performance of a freshly rebuilt system whereas the performance continuously deteriorates with usage. The low correlation of the simulation and measured data for the "end" data case highlights this deviation in Figure 7. Figure 7 reiterates the observations made in Figure 6 and suggests that the GRNN can also be used for the engine performance analysis. The effect of a 10 neuron hidden layer was also found to be insignificant.

Figures 6 and 7 throw meaningful lights on the turbine performance when the simulated load data is compared with the measured value for three data sets, namely 'begin', 'intermediate' and 'end' data sets collected after 3, 17 and 35 months of operating after a major overhaul. Ideally, the data points should scatter around one for healthy and normal state as simulated by the ANN models. The simulated results for different test data sets formed clusters that can be further analyzed for anomaly detection. Interestingly, the predictions are fairly close around one for all cases except 'intermediate' group (17-18 months data). These data points can be seen as widely scattered and seems to represent an anomaly and potentially indicating an unhealthy state. This can be explained by the fact the seasonal variation in the energy requirement and lower gas pressure generates lower unit load during this time period. This is confirmed by the Figure 9 where it is evident that the gas pressure and unit load for this data set are well lower than that used for training the models. Hence the ANN models trained at peak performance may not be able to predict the consistently for lower performance.

An alternative way to reassess the simulation results is by estimating means as shown in Figure 7. These means are based on at least 15 iterations and may be seen to be fairly consistent except the intermediate case. The deviation of means is around 15 to 25 percent lower than the expected values. Figure 7 also includes a few data points that come from GRNN model with 10 neurons at the hidden layer. No significant effect on the mean output is evident as compared to 20 neurons results.

In order to study the feasibility of anomaly detection using the deviation between the measured and simulated unit load, a threshold is introduced based on the measured load variation. A probabilistic level for the measured load will provide the chance of detecting the fault based on the usage state of the engine. The probability for the load yielding variations of 10, 20 and 30 percent of the measured power

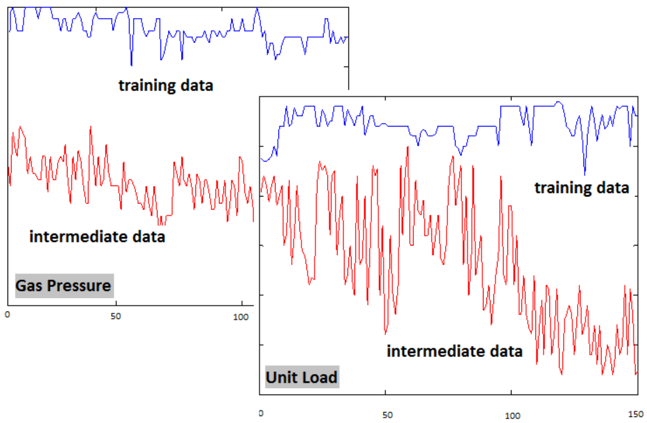

Figure 9: Comparison of the measured input gas pressure and output unit load data (both scaled) for the training and intermediate data set

of the gas turbine is estimated. Table 1 gives the results of the probabilistic analysis supporting our qualitative anomaly/no anomaly observations for predictions with quantitative (probabilistic) measure of load variations. As for example, setting the criterion at 20 percent load variation, the intermediate stage will have around 36 percent probability for anomaly detection. The two usages namely begin and end stages should have almost no chance for anomaly detection. Intermediate test data significantly contributes to the probability of variation dues to its lower magnitude compared to the other data sets and confirm the anomaly and under utilization of the GT capabilities even if it is deliberate.spacing between paragraphs. All papers should use Times Roman 10-point font throughout.

Load variation	begin	intermediate	end	training
10 %	6.0 %	68.5 %	3.9 %	4.8 %
20 %	0 %	36.5 %	0.83 %	0.33 %
30 %	0 %	17.5 %	0 %	0 %

Table 1: Computed probability level for the measured load

6. Conclusion

Artificial neural network models have been used for the performance based anomaly detection of a small sized gas turbine. Four independent input variables and output variables were selected from the operating and performance data. The health monitoring data was collected over the entire operational time between two major overhauls and used for ANN model training, validation and testing. However, the output power was considered as the major performance index for this study, as the four output models were not effectively trained for the selected data sets. Back propagation (BPNN) and generalized regression (GRNN) neural network models were implemented with MATLAB™ programming for this work. Both the models appear to well capture the behavior if the output unit loads. The comparison of the test data set collected 17 months after engine overhauling and its ANN based simulation represent an anomalous situation. The difference in the output unit load may be due to the deliberate lower gas pressure adjustments made to accommodate seasonal variation in the power requirement. Otherwise, the scatter between the simulated and measured unit load increases with usage suggesting that the trained ANN representing the performance of a freshly rebuilt system can be used for anomaly detection. A high probability level over 36 percent is estimated for variation of the rated power capacity of the GT engine. However, samples collected towards the end of the entire operation cycle indicate no unhealthy signs.

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BIOGRAPHIES

Dr. Amar Kumar has more than 25 years of research and consulting experience in the fields of structural materials characterization and development, fracture mechanics, failure analysis and applications. Dr. Kumar is currently working as senior research scientist in the development projects of diagnostics, prognostics and health management of aeroengine components. He specializes in both data driven approaches and physics based modeling and simulations. Dr. Kumar has published more than 170 research papers in refereed journals, conference proceedings, and technical reports.

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Avisekh Banerjee, PhD, PEng, is Senior Mechanical Engineer at Life Prediction Technologies Inc. (LPTi), Ottawa, ON. He is working on the development of a diagnostics and prognostics tools for turbo-machinery and avionics. His area of research and interests is diagnostics, prognostics and data trending for failure detection and development of PHM framework.

Alok Goel has more than 30 years of manufacturing, research, and industrial experience. He has a M.Sc degree in Advance Manufacturing Systems & Technology from University of Liverpool, UK. His research interests are in naval fuel filtration and lube oil separation. He is specialized in manufacturing graded natural fiber as a filler material for plastic reinforcement application.