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A Novel Proposed Neural Network MAD (Monitoring, Analysis and Diagnose) Model for Industrial Gas Turbine

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Abstract: Monitoring, analyzing and diagnostic faults of industrial gas turbine are not an easy way by using conventional methods to complexity of faults. Artificial neural network is deem an active tool to analysis and diagnose faults. Here, we suggest an efficient neural network model due to monitor, analysis and diagnose faults of the gas turbine engine for on-line treatment with a twofold advantage. First, the model is able to diagnose the fault in case of uncertainty or corrupted data by using semi-intelligent artificial neural network. Second, it can predict the extent of the deterioration of the performance efficiency of the turbine engine by using intelligent artificial neural network through a simple GUI. The experiment has been done on five faulty conditions and the proposed neural network model tested with new dataset. The results have proven that, the proposed model produced satisfactory results with 10-10 Mean Square Error (MSE) that considered optimal results when compared with training data sets.

Key words: Gas turbine, artificial neural network, fault diagnosis system, graphical user interface, fault monitoring system, fault analyzing system

INTRODUCTION

Today, most of factories run the components of Gas Turbine (GT) at full operation in order to simulate the demands of the market which lead to the deterioration in the performance of the engine. Therefore, it is necessary to make a periodically maintenance work in order to avoid any breakdowns that has a significant effect on the production and to avoid any fault to grow up. Therefore, a developed monitoring system to the engine components using Artificial Neural Network (ANN) is suggested in this research and through measurements analysis, the faults can be discovered early and take the necessary precautions.

ANNs are massively parallel-interconnected networks that have the capability to perform pattern recognition, classification and prediction (Kumar *et al*., 2014). Many problems faced researchers can be fixed by neural network models that is principally helpful in cases such as simulation, fault diagnosis and sensor validation of power plants (Olausson, 2003; Arriagada, 2003). Relation between input and output seem complicated through modeling. Therefore, an ANN nonlinear statistical data modeling tools are considered in a simple way in which the network is trained to learn in a recognition instituted on the input and output (Arriagada *et al*., 2002). ANN application has proved its efficiency in monitoring, analyzing and diagnosing faults in the scope of combined power plant when compared with traditional methods (e.g., thermo dynamical and frequency-based modeling).

These methods are considered non-intelligent long methods for system monitoring to predict faults that produce an inaccurate system analysis (Wang *et al*., 2012; Lee *et al*., 2010). However, in this study proposed an intelligent model for system monitoring to predict faults that produce an accurate system analysis, helping to diagnose faults properly. Using data from available GT in a variety of industrial power plants through neural network models in case of the engine performance data are not available the simulated data can be generated by software engineering.

In this case, the information is entered to the software to make a preliminary model for data generation. Finally, this data include the entire domain of the system. Fault diagnosis system is the system of performing the tasks of detecting, isolating and identifying the type of fault through the monitoring and analyzing process (i.e., monitoring one or all parameters in the engine can facilitate the discovery of the deterioration at an early stage).

Fault detection refers to make a binary decision-either that something has gone wrong or that everything is fine (Hwang *et al*., 2010). While, fault isolation refers to detect

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the state of defect component between system components (Sobhani-Tehrani and Khorasani, 2009). Therefore, monitoring and analyzing are essential tools in the early fault detection. This study proposed Artificial Neural Network Model (MAD) for monitoring, analyzing and diagnostic system developed to evaluation the gas turbine engine performance through a simple GUI.

Literature review: Nowadays, ANN becomes strong tool for researchers in industrial systems to obtain trustworthy solutions. Increased the industrial system efficiency requires the operation of monitoring and diagnosing of different faults.

These operations need a substantial experience and man-hours due to monitor the plant and locate the associated faults. Therefore, ANN considered an active ANN to model the performance of a simple gas turbine and the results provided by thermodynamic models using heat and mass balance programs. They have proven that, ANN are powerful tools for performance prediction as well as generation of accurate power plant model.

While in this study, the work is built upon a mathematical model for gas turbine engine that determines the relation between inputs and outputs by using neural network. By Mesbahi *et al*. (2001) presented an empirical model by neural network system in which predicted values are compared with real results. In this study, the neural network model tested with a new dataset (i.e., that are different from data used in the training process) and the results compared with the results of training model.

ANN can be used in the workplace to monitor the system, diagnose faults and system identification (Arriagada *et al*., 2003a, b; Bourquin *et al*., 1998). For this reason, a neural network mode proposed to monitor the system, easily detect and diagnose the faults. The researchers by Fast *et al*. (2008) applied ANN for monitoring gas turbine in maintenance system based on simulated data. By Fast *et al*. (2009a, b), the researchers used a neural network and Cumulative Sum (CUSMUS) for monitoring and detecting of deterioration in the performance of industrial gas turbines but it has some limitation as it does not have the ability to handle different load level transient operation and false alarm rates. A neural network model to diagnose faults of medium-size industrial gas turbine is presented by Arriagada *et al*. (2003a, b) while a study to detect and isolate faults on an industrial gas turbine model by neural network is showed by Simani and Patton (2008). The resaerchers, Guez and Selinsky (1988) and Tu (1996) discussed the main advantages and disadvantages of using artificial neural network in modeling techniques even if the data is incomplete.

Therefore, it is necessary to develop a neural network model for training set of data based upon the mathematical model that is used to simulate the faulty data to monitor the gas turbine engine for on-line processing.

MATERIALS AND METHODS

Neural network model for gas turbine: Neural network model for gas turbine can be generated by using different techniques based on the underlying network structure and associated training algorithm.

Therefore, the preferable structure for ANN is the one that can expect dynamic behavior of the system as precisely as probable based on some basic steps (Asgari, 2014). One of the main steps of neural network model is data acquisition and chosen variables. This step is considered as a first step on modeling and controlling industrial system depending on neural network.

In which the neural network model can be constructed directly using the performance data from an actual gas turbine available in a variety of industrial power plants. When an operational data are not available, a simulated data can be generated by software engineering. This data is fed to the network to make a preliminary model for data generation as proposed in this study. The obtained data should cover the whole operational range of the system and all passing data during start or stop processes should be removed from the collected data before the modeling process.

The best choice of modeling process of the non-linear behavior of power plant systems and power plant components is based on Multi-Layer Perceptron neural network (MLP) (Arriagada *et al*., 2002, 2003; Olausson *et al*., 2003). The MLP is a multi-layer feed-forward networks that have at least two layers of computation neurons, one of them is hidden (Krose and Smagt, 1996).

It is important in the training process to choose the appropriate number of hidden layers and available neurons in each layer. Although, the number of hidden layers is decided based on trial-and-error, one hidden layer is enough to approximate any continuous function. In this research, we proposed a model for monitoring, analyzing and diagnostic gas turbine as shown in the following sections.

Monitoring model for gas turbine performance deterioration: Monitoring model for gas Turbine performance deterioration. In the proposed neural network model, eight input variables are selected for input layer (i.e., measurements) and five output variables are chosen

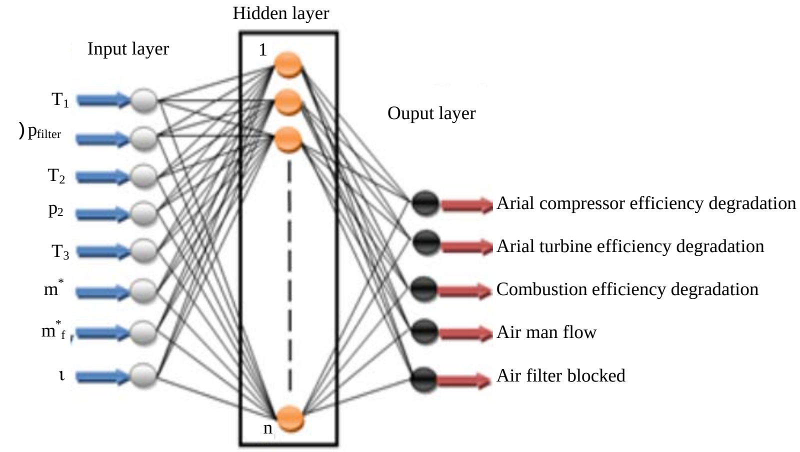

Fig. 1: Proposed NN Model with input, hiden and output layer

for the output layer. The model based on the mathematical model of thermodynamic process. The basic factor of thermodynamic principle of gas turbine operation is the selection of input and output variables.

Input layer and output layer for proposed neural network model:

- Compressor inlet temperature (T_1)
- Compressor discharge temperature (T_2)
- Compressor discharge pressure (P_2)
- Engine mass flow rate ($m^{\cdot}$)
- Inlet turbine temperature (T_3)
- Fuel mass flow rate ($m^{\cdot}_f$)
- Engine load (L)
- Filter differential pressure (Δp_{filter})

Output layer for proposed neural network model:

- Axial compressor efficiency degradation
- Axial Turbine efficiency degradation
- Air mass flow
- Combustion efficiency degradation
- Air filter blocked

Figure 1 shows the NN Model with input layer, one hidden layer and output layer (Sigo *et al*., 2017). The proposed monitoring model for gas turbine using neural network consists of three main stages as follows. The main aim of the propose NN Model is to reach an appropriate data sets for training the network based on the results of mathematical model that used for system analysis. To determine the optimal length of the learning process, the network training goes on until the validation error (i.e. which is continuously monitored) starts to increase as illustrated in the proposed algorithm below. In the algorithm, a log-sigmoid transfer function is used in the hidden layer and pure linear transfer function is used in the output layer.

Updating weights is based on a gradient descent method for minimizing the error function (Fast and Palme, 2010). The number of neurons at hidden layer is carried out by a trial-and-error procedure. According to the proposed NN Model, the best choice of hidden neurons is 6~80 in which the training algorithm stopped before the maximum number of epochs reached to avoid overtraining of the neural network.

Gas turbine measurements analysis model

Gas turbine measurements analysis model: The accuracy in the ANN Models performance depends on the input data.

So, any fault in the input data due to single sensor failure leads to incorrect degradation detection. Herein, an alternative solution to complete the degradation detection is introduced regardless the reading of the failed sensor. The second main point of this paper focuses on the analysis model that can be applied for each single faulty sensor. Each element (i.e., sensor reading) is compared with its valid range (e.g., maximum and minimum values)to determine which of them is failed. If the sensor reading falls within its valid range then, this reading is correct. Otherwise, some correction must be carried out by constructing an ANN between the faulty reading and the remaining measurements.

The training data is obtained from the thermodynamic model (4032 dataset). Figure 2 shows an example of analytic ANN Models for the fourth input element (i.e., pressure ratio) which is integrated from one hidden layer consists of ten neuron of this hidden layer and

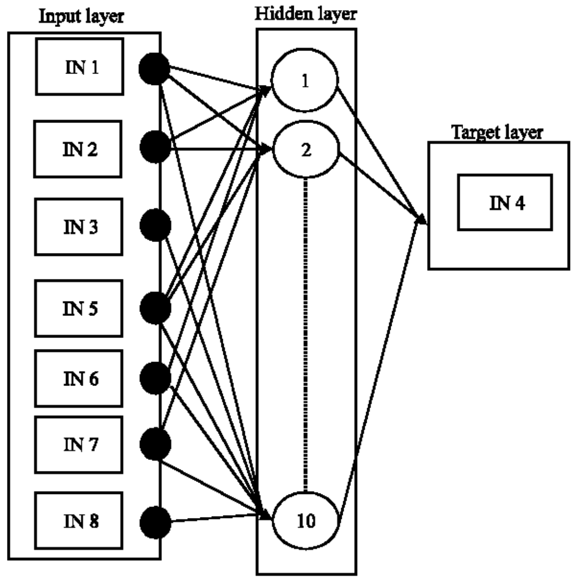

Fig. 2: Analytic model for the presdsyure ratio

used logistic transfer. By this way, the eight ANN Models (i.e., number of measurements) have been developed. These models were tested with all training data which gave accurate results with accepted percentage error.

These eight ANN Models have been merged with degradation detection ANN Model to construct an integrated intelligent system for industrial gas turbine engine degradation detection model. The proposed NN measurements analysis algorithm is illustrated below.

In this model, we have eight sensors reading measurements that represent the eight input data as shown in Table 1 and 2. Figure 3 illustrates the flow chart for degradation detected with input measurement analysis algorithm.

Experimental results and performance analysis: To test the efficiency of the proposed NN monitoring model, a range of data sets trained by the neural network toolbox using MATLAB. Related to the above algorithm, the performance analysis of proposed NN Model is shown in Fig. 4. The MSE in Fig. 4 decreased with increasing the number of epochs (i.e., from 100-700 epochs).

After that, the MSE reaches a stability condition 10-11 and the training algorithm stopped automatically according to the unchanged in the weights (i.e., optimality case in the proposed algorithm). The historical and current prediction of NN system model is accessible

Table 1: The stage of the proposed monitoring model for gas turbine

Stage	Processing
Training	Includes the calculation of neural network weights that determined by randomly initializing connection weights The selection of input data and chosen output variables are presented in this stage. One hidden layer was chosen and the network was optimized regarding the number of neurons in this layer (Asgari *et al.*, 2013)
Validating	This stage includes measuring the network's performance during training according to a certain conditions (Sigo *et al.*, 2017) (e.g., Max epochs = 1000 or MSE reached 10^{-11}). When it does not have any notable progress, the training process stops
Testing	The test set provided to the network to ensure that a correct generalization capability has been obtained. In the proposed model, a new data set that was different from data which used in the training process is provided

Table 2: Sensor data measurements

Sensor No.	Input data
1	Compressor Inlet temperature
2	Air inlet filter
3	Engine flow rate
4	fuel flow rate
5	Compressor discharge temperature
6	Compressor pressure ratio
7	Turbine discharge temperature
8	Engine load

through a simple GUI to estimate a plant performance as shown in Fig. 5. It showed the main components of gas turbine engine associated with the input parameters of the NN Model. This can be used for online monitoring as offline estimation of expected performance of the plant with varying local ambient conditions (Fast *et al.*, 2009a, b). The monitoring model is considered a semi-intelligent to predict the outputs degradation. The results of performance degradation are shown in Fig. 6. Each plot in the figure has 3 marks (e.g., minimum degree, maximum degree and resulting point of degradation). For intelligent system, we apply analysis model to predict the actually value of faulty input as show in Fig. 7.

Figure 7 show, how the intelligence of the analysis model to discover the faulty input and predict the actually value so the results of performance degradation after applying analysis model are shown in Fig. 8. Each plot in the figure has 3 marks (e.g., minimum degree , maximum degree and resulting point of degradation). Figure 8 and 9 illustrate the performance of integrated degradation detected system when running eight times with testing data (i.e., 100 outside training dataset).

For each state, the component degradation has been calculate when one of measurements parameter is inoperative and given irrational values such as zero value.

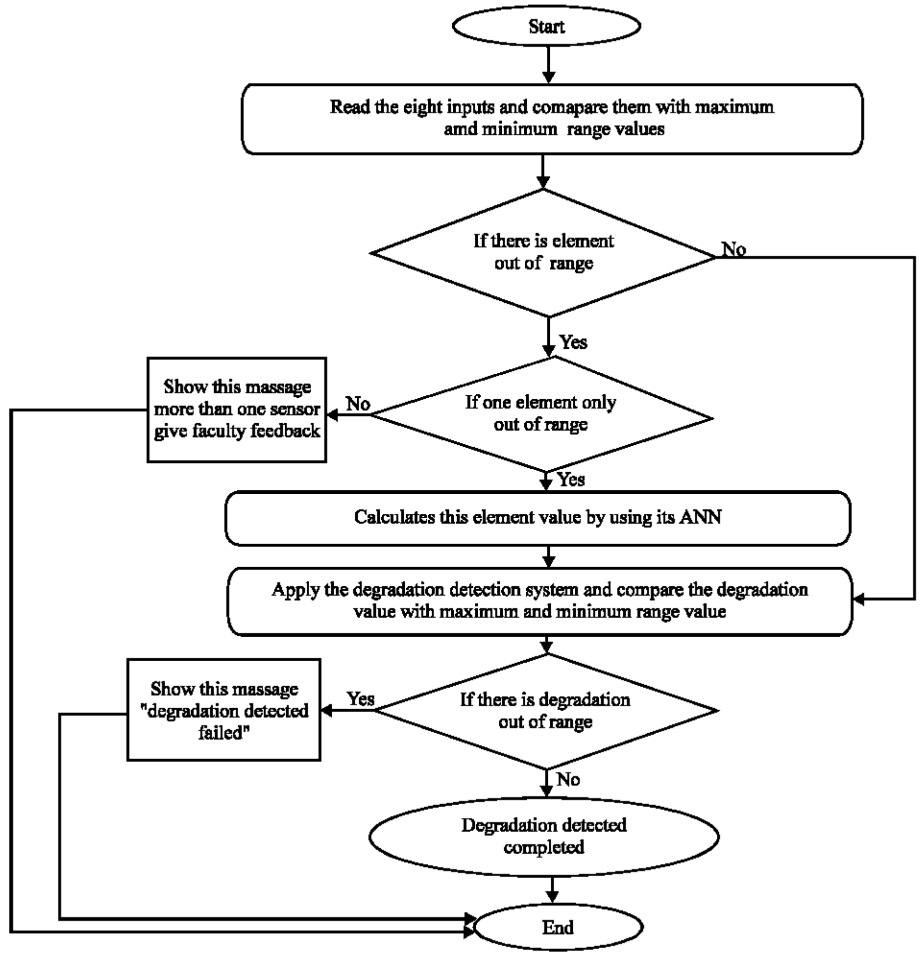

Fig. 3: Flow chart for integrated degrated degradation detected

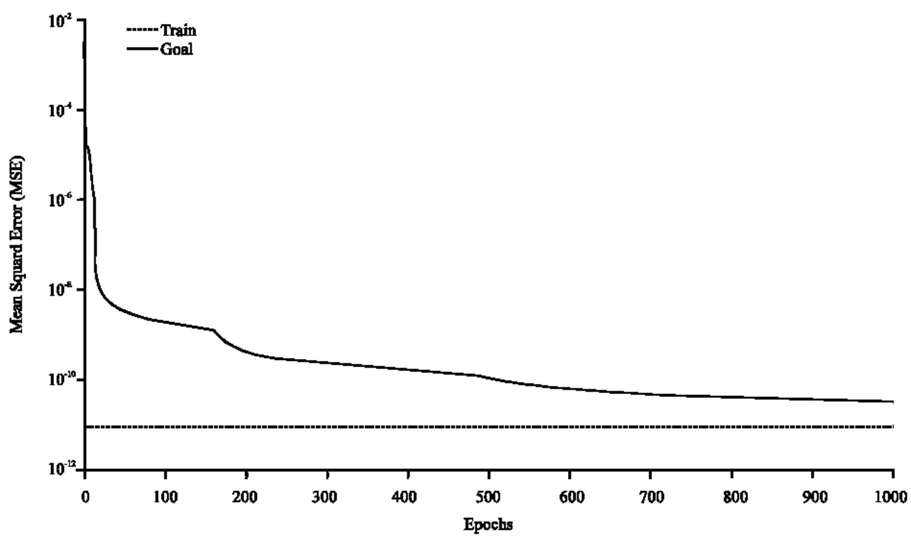

Fig. 4: Performance analysis of NN Model

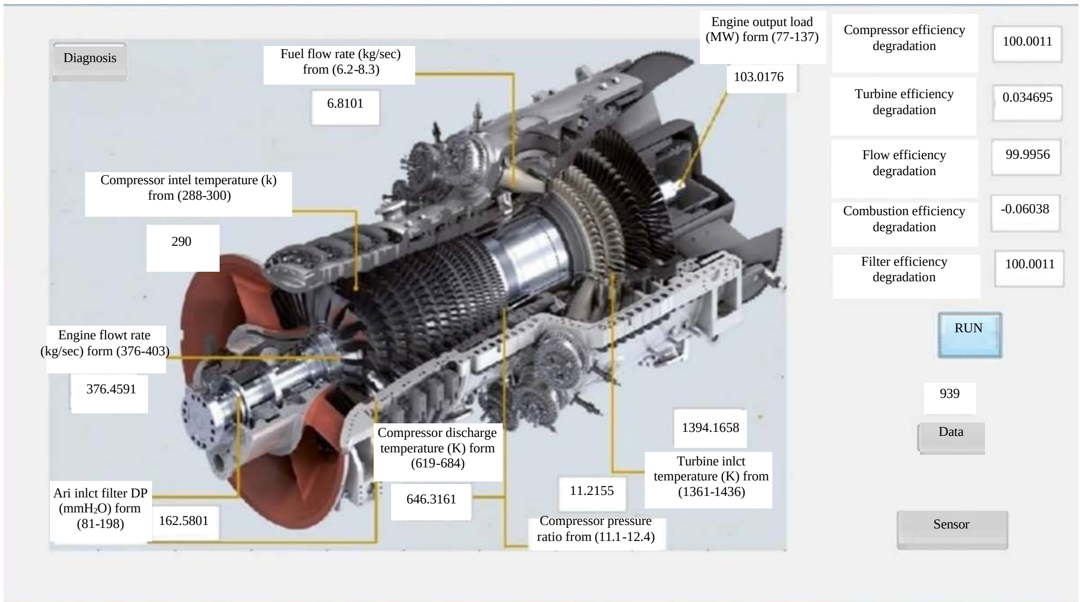

Fig. 5: GUI of NN monitoring model

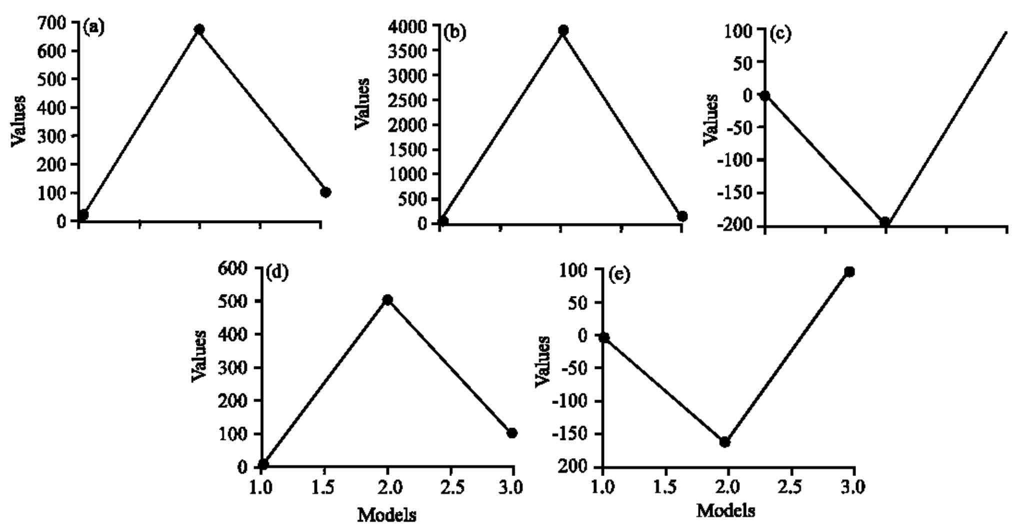

Fig. 6: Diagnosis plot of NN monitoring model

Figure 10 shows the average MSE for all stats of component degradation factors within range 8e-09~2.5e-09. Figure 10 average MSE for all stats of component degradation factors. The proposed model tested with new dataset (i.e., 100 data points) with conditions far from the extent to which it has been trained by the network. The results have proven that, the MSE of the proposed monitoring model within the range 2.5*10-10~ 0.8*10-10 which considered close to the optimal MSE (i.e., more than 99%) as shown in Fig. 11. Table 3 shows the degradation efficiency between the training and testing dataset.

Table 3: Degradation efficiency (new data set)

Output	Degradation (%)
Degradation air filter efficiency	99.99999999673
Degradation of compressor efficiency	99.99999999001
Degradation of turbine efficiency	99.99999999989
Degradation of flow capacity efficiency	99.99999998627
Degradation of combustion efficiency	99.99999999131

The experimental results have proven the efficiency and effectiveness of the proposed neural network model in monitoring and diagnosis faults of gas turbine engine.

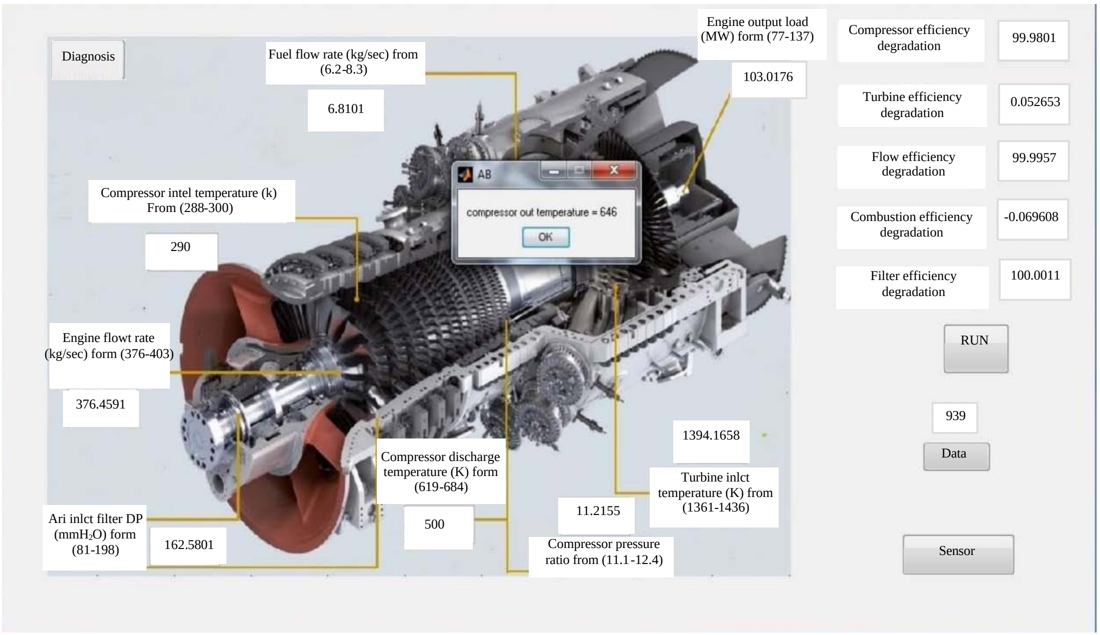

Fig. 7: GUI of NN analysis model

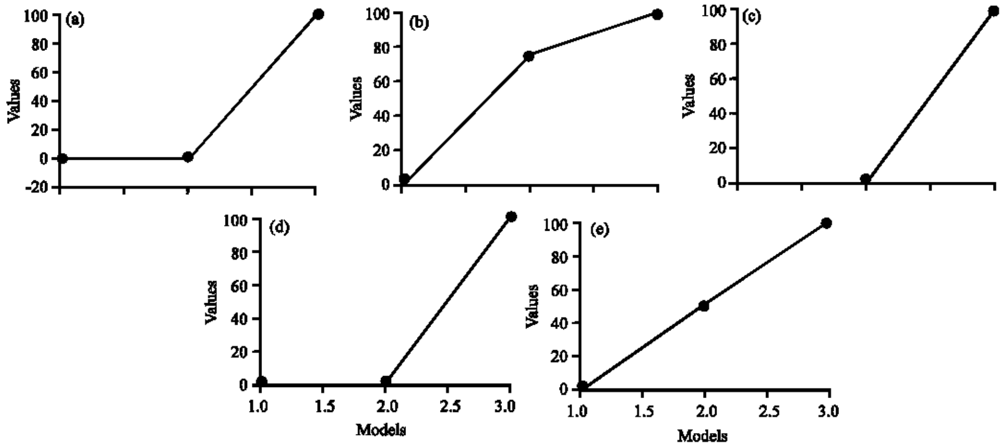

Fig. 8: Diagnisis plot of NN analysis model

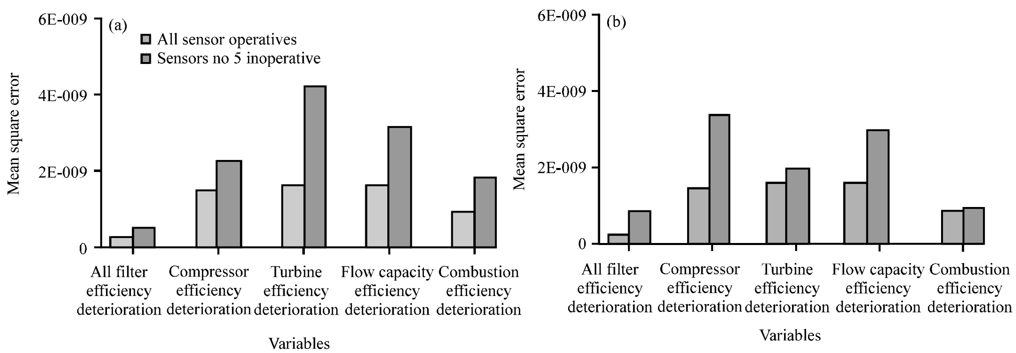

Fig. 9: Continue

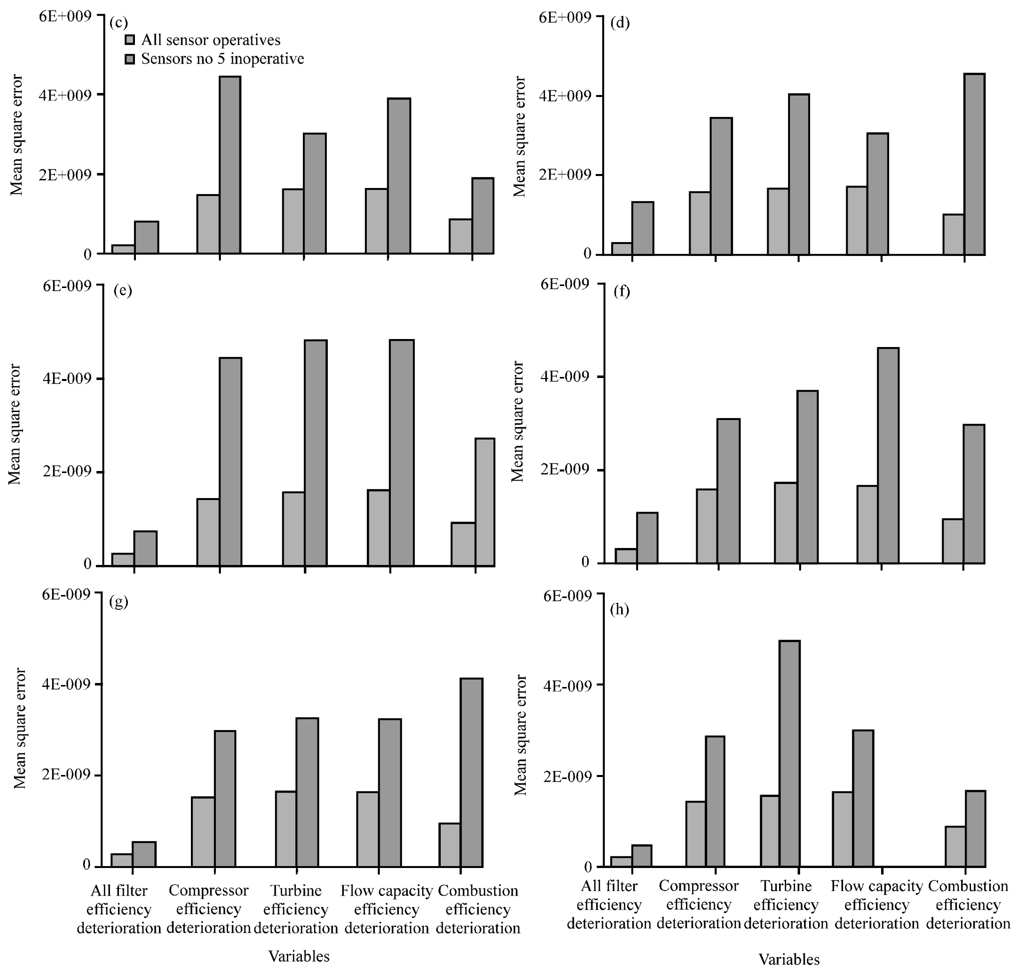

Fig. 9: MSE between engine model and degradation detection system: a) At sensor 1= 0; b) At sensor 2 = 0; c) At sensor 3 = 0; d) At sensor 4 = 0; e) At sensor 5 = 0; f) At sensor 6 = 0; g) At sensor 7 = 0 and h) At sensor 8 = 0

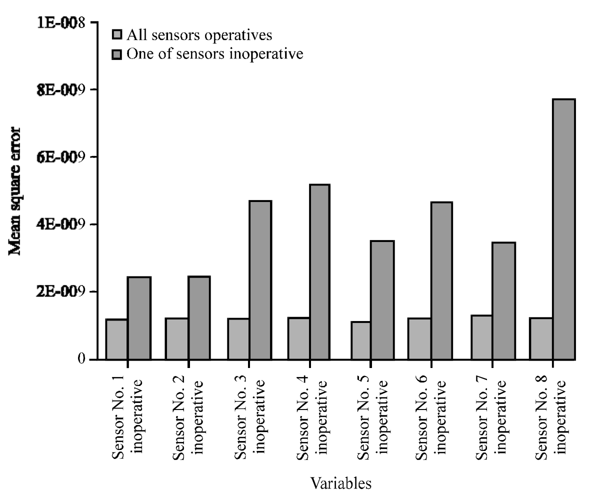

Fig. 10: Average MSE for all stats of compontent degradation factors

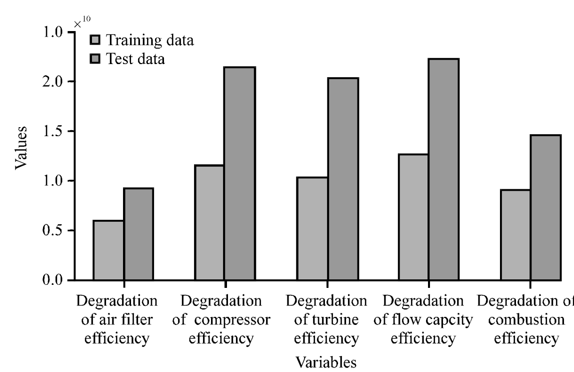

Fig. 11: Performance analyses with new data set

CONCLUSION

Today, most of factories run the components of GT at full operation in order to simulate the demands of the market which lead to the deterioration in the performance of the engine. Therefore, system monitoring is primary to refinement mechanical system running condition and the function characteristic and it also plays an important function in obviating breakdown and danger accidents, ameliorative operation reliability and reducing maintenance cost. In this study, a proposed ANN Model for monitoring, analyzing and diagnosing system presented. The data used for training the network obtained from a mathematical model and the results achieved. A simple GUI discovers any sensor inoperative and can also expect the truth value accordingly diagnose faults engine properly. The proposed model has proven its efficiency with new data sets that are close to the optimal performance results.

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