# Neural Network Monitoring Model for Industrial Gas Turbine

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**ABSTRECT--** ***Monitoring and diagnostic faults of industrial gas turbine are not an easy way by using conventional methods due to the nature and complexity of faults. Artificial neural network is considered an efficient tool to monitor and diagnose faults. In this paper, we proposed an efficient neural network model to monitor the gas turbine engine for on-line processing with a twofold advantage. First, the model is able to diagnose the fault in case of uncertainty or corrupted data. Second, it can predict the extent of the deterioration of the performance efficiency of the turbine engine through a simple graphical user interface. 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 that considered optimal results when compared with training data sets.***

**Keywords--** Artificial neural network, Fault diagnosis system, Fault monitoring system, Gas turbine, Graphical user interface.

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## 1. 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 proposed in this paper and through follow up measurements, the faults can be discovered early and take the necessary precautions.

Artificial neural networks are massively parallel-interconnected networks that have the ability to perform pattern recognition, classification and prediction [1]. Many problems faced researchers can be fixed using neural network models that are principally helpful in cases such as simulation, fault diagnosis and sensor validation of heat and power plants [2], [3] Relation between input and output seem complicated through modelling therefore considered ANN nonlinear statistical data modelling tools in a simple way. Therefore, the network is trained to learn in a recognition instituted on the input and output [4].

ANN application proved its efficiency in monitoring and diagnosing faults in the field of combined heat and 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 [5], [6].

Using data from available GT in a variety of industrial power plants, we can generate neural network models, when the operational data are not available, the simulated data can be generated by software engineering. In this case, the information is fed to the software to make a preliminary model for data generation [7]. Finally, this data should 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 process (i.e., monitoring one or several 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 [8].While fault isolation refers to determine the location of faulty component among various components of a system [9].

Identification of the fault estimates the size of the fault and determines the time of onset of the fault. Therefore, monitoring is an essential tool in the early fault detection. In this paper, a proposed NN monitoring model developed to estimate the gas turbine engine performance through a simple GUI.

## 2. LITERATURE REVIEW

Nowadays, ANN becomes one of the most important challenges of researchers in industrial systems to obtain efficient and reliable solutions. Improving the efficiency of an industrial system requires the operation of monitoring and diagnosing of different faults. These operations need a substantial experience and man-hours to monitor the plant and locate the associated faults. Therefore, ANN considered the most suitable tool to do this through learning.

The authors in [10] used an artificial neural network 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, artificial neural networks are powerful tools for performance prediction as well as generation of accurate power plant model. While in this paper, the work is built upon a mathematical model for gas turbine engine [11] that determines the relation between inputs and outputs by using neural network.

The authors in [12] presented an empirical model by neural network system in which, predicted values are compared with experimental results and a good correlation was observed. In this paper, 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 [13], [14].For this reason, a neural network model proposed to monitor the system, easily detect and diagnose the faults.

Other researchers applied ANN for monitoring gas turbine in maintenance system based on simulated data [15], [16]. In [17] 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 in [18].While, a study to detect and isolate faults on an industrial gas turbine prototype using artificial neural network is showed in [19].The authors in [20], [21] discussed the main advantages and disadvantages of using neural network in modelling 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 [11] that is used to simulate the faulty data to monitor the gas turbine engine for on-line processing.

## 3.NEURAL NETWORK MODEL FOR GAS TURBINE

Neural network model of gas turbine can be generated by using different techniques depending on the underlying network structure and associated training algorithm. Therefore, the preferable structure for ANN is the one that can expect dynamic behaviour of the system as precisely as probable based on some basic steps [22].

One of the vital steps of neural network model is data acquisition and chosen variables. This step is considered as a first step on modelling and controlling industrial system based on neural network. In which, the neural network model can be created directly using the operational 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 paper. 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 modelling process.

The best choice of modelling process of the non-linear behaviour of power plant systems and power plant components is based on multi-layer perceptron neural network (MLP) [4], [13], [23]. The MLP is a multi-layer feed-forward networks that have at least two layers of computation neurons, one of them is hidden [24] as shown in Figure1.

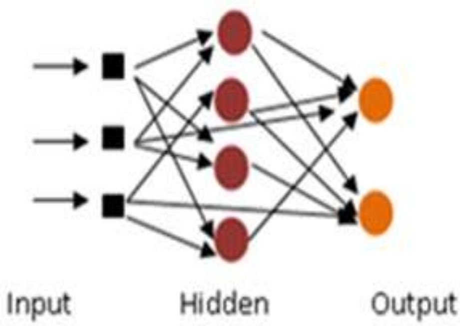


**Figure1**: Structure of MLP

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.

The proposed neural network model of gas turbine is shown in Figure2 with input layer, one hidden layer and output layer based on the mathematical model of thermodynamic process [11]

The basic factor of thermodynamic principle of gas turbine operation is the selection of input and output variables.

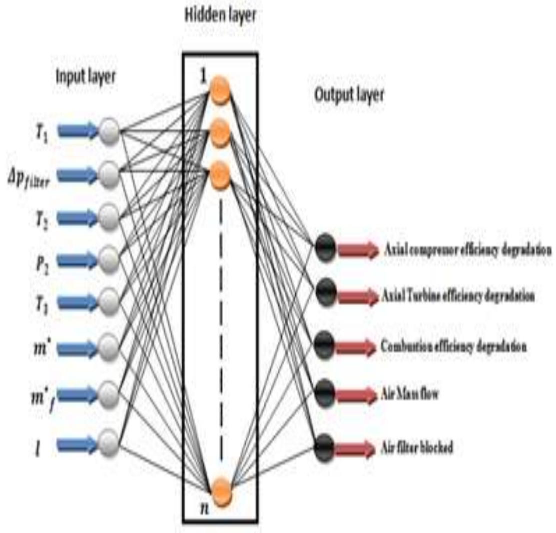


**Figure 2**: Proposed NN model of gas turbine

Therefore, in the proposed model, eight input variables are selected for input layer and five output variables are chosen for the output layer as listed in Table 1 and Table 2 respectively.

**Table 1**: Input variables of NN model

| Symbol | Variables |
|---|---|
| $T_1$ | Compressor inlet temperature |
| $T_2$ | Compressor discharge temperature |
| $P_2$ | Compressor discharge pressure |
| $m^{\bullet}$ | Engine mass flow rate |
| $T_3$ | Inlet turbine temperature |
| $m^{\bullet}{}_f$ | Fuel mass flow rate |
| $L$ | Engine load |
| $\Delta p_{filter}$ | Filter differential pressure |

**Table 2:** Output variables of NN model

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

The proposed neural network model for gas turbine consists of three main stages as follows.

- Stage 1(training): This stage 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 [16].
- Stage 2(validating):This stage includes measuring the network's performance during training according to a certain conditions [25] (e.g., Max epochs=1000 or $MSE$reached$10^{-11}$). In case if it does not have any notable progress, the training process stops.
- Stage 3(testing):In this stage, 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.

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 [11] 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 according to the monitoring algorithm as illustrated in Figure 3. In which, 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 [26].

Algorithm: Proposed NN monitoring algorithm
Input: Set of eight inputs$x_{i,i=1\ldots,8}$ associated with weights initialized randomly
Output: Set of five outputs variables$o_{j,j=1\ldots,5}$

Steps:

While (No of epochs< 1000) do

1- Compute the weighted sum of inputs $x_i$(at input layer)
2- Pass the result to the transfer function through hidden layer and get the output values $o_j$ (at output layer)
3- Compute $MSE$ according to the following formula.

Where,$t_j$ is the target for each output variable and$n$is the total number of data set.

4- Check the network performance

If($MSE\leq$ $10^{-11}$&& the weight doesn't change)

Then, stop and go to step 5

Else, update weight automatically and go to step (1).

5- End.

**Figure 3:** NN Monitoring algorithm

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.

## 4. EXPERIMENTAL RESULT AND PERFORMANCE ANALYSIS

To examine the efficiency of the proposed NN model, a range of data sets trained by the neural network toolbox using Matlab. According to the above algorithm, the performance analysis of proposed NN model is shown in Figure 4.

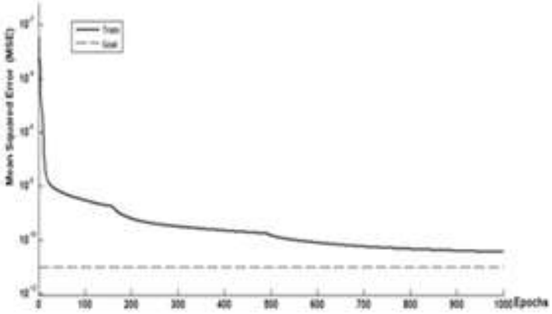


**Figure 4**: Performance analysis of NN model

The MSE in Figure.4 decreased with increasing the number of epochs (i.e., from 100 to 700epochs). 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 model is accessible through a simple GUI to estimate a plant performance as shown in Figure 5. It showed the main components of gas turbine engine associated with the input parameters of the NN model. The model is able to predict the outputs degradation according to table 2 and monitor the gas turbine performance.

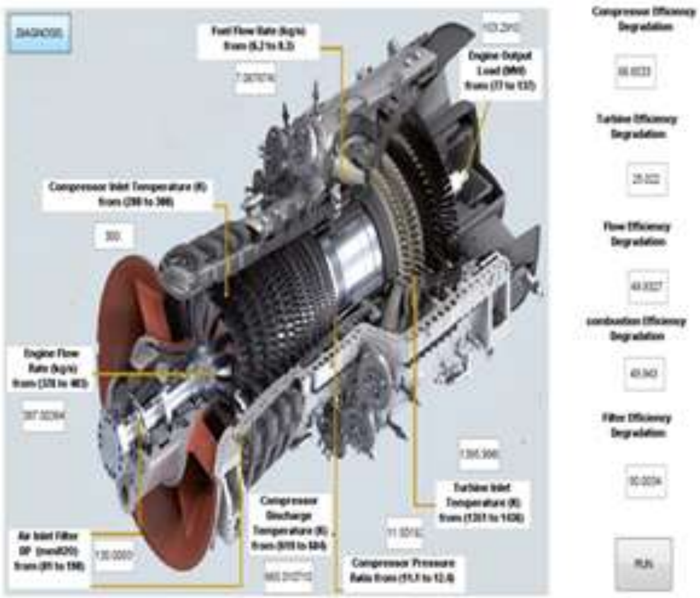


**Figure5**: GUI of NN monitoring model

This can be used for online monitoring as well as offline estimation of expected performance of the plant with varying local ambient conditions [27]. The results of performance degradation are shown in Figure 6.

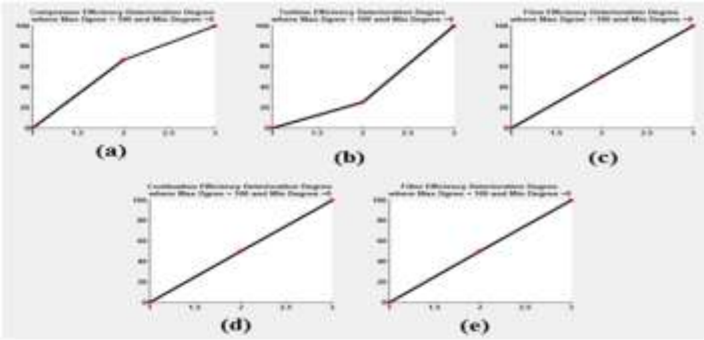

**Figure 6**:Diagnosis plot of NN model

Each plot in Figure 6 has 3 marks (e.g., minmum degree , maximum degree and resulting point of degradation).For example in plot (5-a), the compressor efficiency deterioration max degree is 100 and min degree is 0 and the resulting point is 66. That is mean compressor efficiency deterioration is66%.

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, theMSE of the proposed model within the range $2.5*10^{-10}$~ $0.8*10^{-10}$which considered close to the optimal MSE as shown in Figure 7.

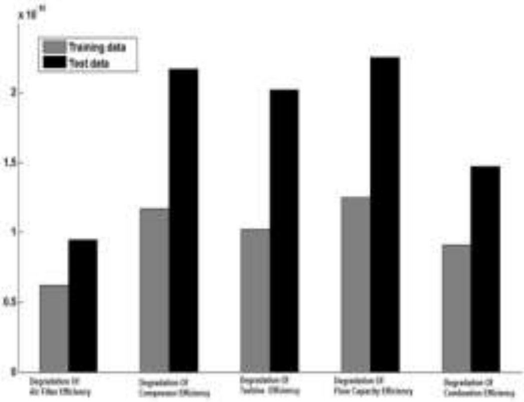

**Figure7**: Performance analysis of new dataset.

The above figure shows the performance analysis of degradation efficiency of the proposed NN model with new dataset and how the results are closed to the optimal ones with more than 99%. Table 3 shows the degradation efficiency between the training and testing dataset.

**Table 3**: Degradation efficiency of new data set

| Output | % of 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 experiemantal results have proven the efficiency of the proposed neural network model in monitoring and diagnosis faults of gas turbine engine.

## 5. CONCLUSION

Fault diagnosis and monitoring are important ways in an industrial gas turbine engine. Therefore, a neural network model proposed for fault diagnosis with a simple GUI based on a thermodynamic model to calculate the engine performance. The NN model calculates the engine performance rapidly and diagnoses the engine components degradation. Through the simple GUI, the engine performance calculated with option to select the thermodynamic model or ANN model. The results of proposed NN model are compared with new dataset and showed that, results are closed to the optimal ones with more than 99%.

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