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# Performance Prediction of A Power Generation Gas Turbine Using An Optimized Artificial Neural Network Model

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***Abstract*— This paper introduces an innovative application of an Artificial Neural Network (ANN) based model for the performance prediction of a power generation gas turbine. this approach optimizes the ANN model by utilizing a comprehensive database to compare various ANN topologies. Based on optimization results, a two-layer Multi-Layer Perceptron (MLP) was constructed and used as the best-optimized topology for such applications. The training dataset comprises historical operational data from a Rolls-Royce (RB21-24G) gas turbine unit. Notably, this model shows substantial accuracy for different ambient conditions and variable power ratings. Furthermore, a sensitivity analysis using various methods was introduced to study the impact of each input on the model outputs. To validate the model's reliability and novelty, we introduce a degradation study, comparing one-year-later on-site operational data with predicted values generated by the ANN model. Remarkably, the results demonstrate strong consistency between measured data and model predictions.**

***Index Terms*— Artificial neural network, gas turbine, performance prediction, system modelling.**

## I. INTRODUCTION

Since gas turbines are very important equipment, their maintenance becomes critical as well. Preventive maintenance based on equivalent running hours is considered costly and time delay factor, which is not favoured by such equipment owners. Hence, condition-based maintenance becomes more reliable and applied in such applications and it becomes of interest to both manufacturers and owners of gas turbines [1]. Many approaches have been introduced by researchers to develop condition-based maintenance theory and application. Monitoring tools that are developed using conventional methods depend on heat and mass balances and thermodynamical maps etc., are considered to be more complicated, general for the specific engine family and more measures need to be taken when used for online monitoring [2]–[4]. Other approaches were introduced for fault diagnostics and system degradation such as studies in[5]–[8].

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The utilization of ANN models to enhance the maintenance and performance options was reported in different applications[9]–[11]. For instance, the authors In[12] introduced a review of different decision-making methods based on information fusion to enhance industrial gas turbine diagnostics. These methods were compared in terms of system fault detection and isolating, concluding a new perspective of a support system for better decision-making. Similarly, the authors in[13] propose a transfer-learning-based gas path analysis method, the suggested method combines operational data with the transfer-learning method in updating the training set for the constructed model, this will maintain higher model diagnostic accuracy.

Moreover, new methods using ANN have started to become widely used in the field of gas turbine applications due to their simplicity, reliability, and specific engine speciality[4]. Operational data of the specific engine is only required for model construction. This data is used to train the ANN model and the corresponding data generated by this model would become a healthy condition reference that can be used for comparison with actual measurements[14]–[16]. However, the issue of lacking data might be an obstacle to constructing a reliable ANN model, hence the authors in [17] developed a model using simulated faulty engine data to generate data, and these data were implemented into the condition monitoring system tool. The study shows this model was capable of predicting all malfunction cases successfully. In their study [10], the authors compared two methods, namely high dimensional model representation (HDMR) and artificial neural network (ANN), to predict gas turbine performance based on operational data. The author suggested using ANN for turbine and compressor condition monitoring due to their lower construction complexity and higher prediction accuracy. Similar work was introduced by [8], [18], [19] to present a condition-monitoring tool using ANN that can be used in gas turbine condition monitoring.

In this work, a novel ANN-based method is studied to be introduced as the foundation for creating a performance monitoring tool applicable to gas turbine systems. Various models are compared and investigated to identify the optimal topology for the application of gas turbine performance studies. This research is built upon operational data obtained from an oil and gas production site, where the RB211-24G unit is used in generating electrical power for block facilities and wellheads. An essential element of this study is the introduction of a degradation study using a year-later dataset. Any deviation of actual measurements from those predicted by the ANN model serves as an indication of potential equipment deterioration or faults. The purpose of this study is to express the reliability and usefulness of using a model based on the ANN method for GT performance prediction and plan maintenance activities accordingly. In the subsequent sections, we detail the methodologies used for constructing and optimizing our model, discuss the research outcomes, and draw conclusions from our findings.

## II. Methods

### *A. System Configuration and Data Management*

Rolls Royce RB 211 is one of two gen-sets which provides electrical power to oil field plants, facilities and wellheads. It delivers up to 23 MW maximum depending on the load required and the ambient conditions, with temperature range from 0 to 45 degrees Celsius and humidity between 10 to 93%. Gas delivered to the turbine is supplied from the central gas processing unit under 42 bar inlet pressure as required by the turbine design. This power generator is a three-spool engine that consists of a gas generator (GG) and a power turbine generator (PT), refer to Fig. 1.

The gas turbine is composed of a skid-mounted mechanical driver system complete with an air intake, filter house and plenum chamber. GG's objective is to deliver hot gas under the desired pressure and temperature to the gas turbine (GT) unit connecting the turbine enclosure and exhaust stack housing of the RB211 gas generator and power turbine. Hence, the power turbine PT is aerodynamically connected to the GG, on the other hand, the electrical generator is coupled to the PT mechanically.

Data has been selected to represent the normal operating conditions of GT power generation. Available operational data were collected from RB211 Gas Turbine based on an hourly rate, about 2199 data points were used, representing two years. In data preparation, all off-mode data and outliers were excluded. Also, transient periods such as the start-up or shutting down of the generator were not included. This will ensure that our model will not be disturbed by these measurements. After loading all data, cleaning and filtering of data were done with NN software tools used for this purpose. Randomization of data is required to ensure training will not be stuck at a local minimum. Also, to make better distribution of data, data is divided into different sets which are training, cross-validation and testing. Normalization and denormalization of data were also done using the NN software during and after the training process.

Ambient conditions including ambient temperature (Celsius degrees), ambient pressure (bar), and ambient humidity (percentage, %), were considered as inputs to the ANN model. Also, generator active power (MW) was considered as an input parameter in the NN model due to its direct effect on all other GT output parameters. Moreover, It is very important for the oil and gas production facility to optimize gas consumption in different processing areas, and to control environmental pollutant sources. Therefore, fuel gas consumption (kW), was studied as an output to the ANN model. Also, exhaust gas temperature (Celsius degrees) was considered as an output parameter. Investigating the compressor side is of importance to determine the overall condition of the GT, so the pressure of low-pressure (LP), and high-pressure (HP) compressors, expressed in (bar), and Variable Inlet Guide Vanes position (VIGV) was included in the output data as well. The basic ANN model configuration is illustrated in Fig. 2.

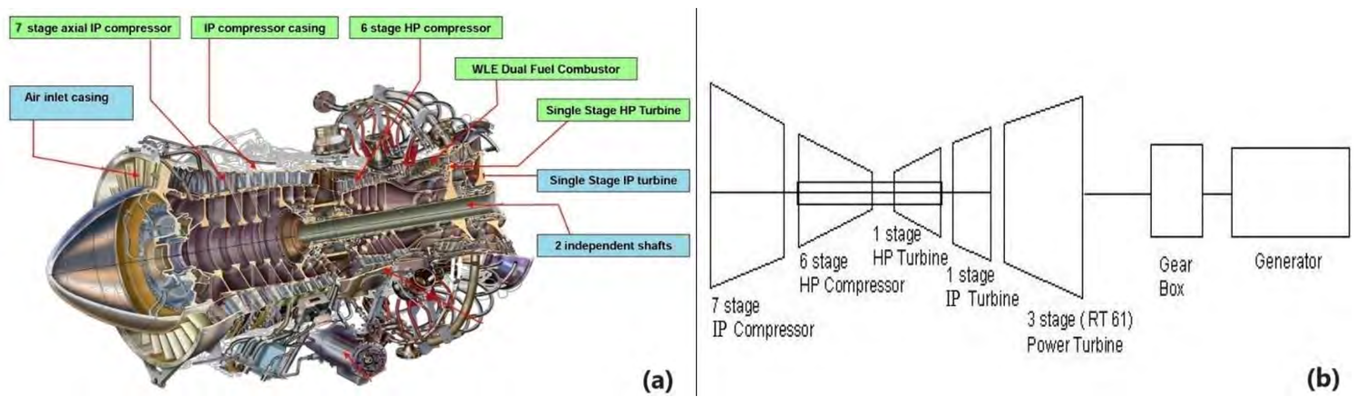


Fig.1. Rolls Royce Gas Turbine, RB 211-24 G, (a) Sectional view, (b) General schematic arrangement[20].

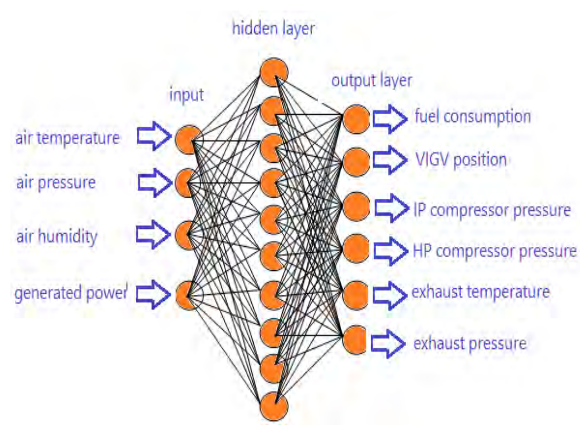


Fig. 2. Schematic illustration for NN Model Topology.

### B. Training, Cross-validation and Testing

The process of creating a single model should go through training, cross-validation and testing. Training and cross-validation determine weight values. While training and updating these values, cross-validation will behave as a supervisor to validate weights. If any deviation happens that causes the Mean Square Error (MSE) to increase above the setting, the software determines to halt the process and the best weight value to be determined, Fig. 3.

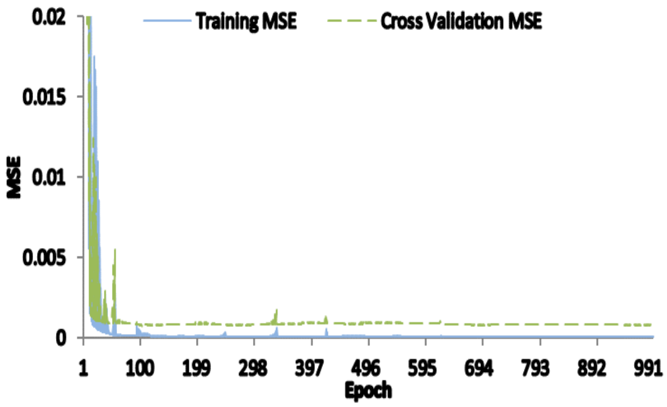


Fig. 3. MSE versus Epoch for training and cross-validation.

In all cases, iterations were set to (1000). Determination of best weights is decided during training, and verified by cross-validation.

Results from Fig. 3. show MSE trending during training and cross-validation. MSE decreases with iteration (Epoch) progress to the final iteration number, where the MSE result was about (0.00004 and 0.0008) for training and cross-validation respectively.

### C. ANN Model Construction

To construct a reliable model, most research on ANN studied and compared different networks with different approaches. Therefore, a variety of network topologies are better to be studied using the database with a different number of possibilities [21]. In this study, an optimization process is conducted to obtain the best NN model for system performance prediction. The first step is done by comparing three model types used for this purpose, these are Multi-Layer Perceptron (MLP), probabilistic Neural Network (PNN) and Logistic Regression Neural Network (LRNN). Every constructed model is compared using the system average prediction error percentage shown in Table 1.

Comparing MLP, PNN and LRNN configurations performance, it is clear that MLP configuration is the best from the point of view that it produced the least error percentage which is identified by:

$$Error\% = \frac{100}{NP} \frac{\sum_{j=0}^{P} \sum_{i=0}^{N} \left| dy_{ij} - dd_{ij} \right|}{dd_{ij}} \quad (1)$$

Where $P$ is the number of output processing elements, $N$ is the number of exemplars in the dataset, $dy_{ij}$ is the denormalized network output for exemplars $i$ at processing element $j$, and $dd_{ij}$ is the denormalized network desired output for exemplars $i$ at processing element $j$. The second step is to optimize and construct the best model topology to determine the other parameters such as layers and weighting factors.

### D. Performance Measures

The methods used in studying the model prediction accuracy are meant to find how close are the predicted values to the actual measurements, the closest results the most accurate is the model. Therefore, results are studied based on the following error-based statistics. The first is the mean square error MSE, which can be found by:

$$MSE = \frac{\sum_{j=0}^{P} \sum_{i=0}^{N} \left( d_{ij} - y_{ij} \right)^2}{NP} \quad (2)$$

Where $y_{ij}$ is the network output for exemplars $i$ at processing element $j$, and $d_{ij}$ is the network desired output for exemplars $i$ at processing element $j$.

The normalized root mean squared error is defined by the following formula:

$$NRMSE = \frac{\sqrt{MSE}}{\sum_{j=0}^{P} \frac{\max(d_j) - \min(d_j)}{P}} \quad (3)$$

The mean square error (MSE) size is used to find the network accuracy, but it doesn't necessarily indicate whether data sets move in the same direction. Thus, by simply scaling the network output, we can change the $MSE$ without changing the data direction using the correlation coefficient (β). Therefore, the correlation coefficient between a network

TABLE 1: ERROR PERCENTAGE COMPARISON BETWEEN MLP NN, PNN AND LRNN.

| | Error% | | | | | |
|---|---|---|---|---|---|---|
| Topology | Total Fuel Demand | Exhaust Temperature | VIGV Actual Position | GG IP Compressor Discharge Pressure | GG H.P. Compressor Discharge Pressure | GG Exhaust Pressure |
| MLP | 0.55 | 0.55 | 1.21 | 0.37 | 0.17 | 0.32 |
| PNN | 0.60 | 0.50 | 1.46 | 0.44 | 0.37 | 0.55 |
| LRNN | 2.67 | 1.57 | 5.66 | 2.17 | 1.96 | 3.17 |

output y and a desired output $d$ is defined by:

$$\beta = \frac{\frac{\sum_i (y_i - \bar{y})(d_i - \bar{d})}{N}}{\sqrt{\frac{\sum_i (d_i - \bar{d})^2}{N}} \sqrt{\frac{\sum_i (y_i - \bar{y})^2}{N}}} \tag{4}$$

where $\bar{y}$ and $\bar{d}$ are the average values of the network output and the network desired output respectively. The correlation coefficient is confined to the range [-1,1]. When β =1 there is a perfect positive linear correlation between y and d they covary, which means that they vary by the same amount. When β =-1, there is a perfectly linear negative correlation between y and d, that is, they vary in opposite ways (when y increases, d decreases by the same amount). When β =0 there is no correlation between $y$ and $d$, i.e., the variables are called uncorrelated. Intermediate values describe partial correlations. For example, a correlation coefficient β of 0.88 means that the fit of the model to the data is reasonably good.

## III. Results and Discussion

### *A. Model Optimization*

The resulting optimization model was a Multi-Layer Perceptron with two hidden layers. A score of (97.094) was given for the best model, the model number was (696) among (781) overall models investigated. The best-recommended topology is MLP with two layers using the Resilient Backpropagation (RPROP) learning algorithm, this model has the criteria listed in Table 2.

The results of the optimum ANN model are shown in Table 3. The results present the performance table reports including the mean-squared error (MSE), normalized root-mean-squared error (NRMSE), mean absolute error (MAE), minimum absolute error, maximum absolute error, and correlation coefficient (β) and scores for the predicted output variables.

The results show high correlations β numbers for inputs to the output, even though it was moderately less in the Exhaust temperature term. Also, error terms show satisfactory values relative to the actual data values, this gives us an indication of model quality and depending on the statistics, one can implement this model for performance predictions.

The score here gives the reader an indication of all statistical numbers included in Table 3. High scores are shown for almost all outputs, except for exhaust temperature which shows fewer scores but still a very good indication of model learning.

Table 2: Best Model (MLP NN) structure and topology.

| Main topology structure | MLP NN |
|---|---|
| No. of layers | 2, (1 hidden layer and 1 output layer) |
| perceptron | 10 |
| transfer function | tanh |
| learning rule | RPROP |
| max. epochs | 1000 |
| error criterion | MSE |
| termination | determined using cross-validation |

### *B. Sensitivity Analysis*

Sensitivity analysis is a test that aims to measure the influence and importance of each input parameter on the outputs. In this test, neither the model configuration nor the topology would be affected. It is based on fixing all input parameters while the desired input is changed to study its effect on outputs. This is done by two methods in this research for robust and reliable results, these methods are:

#### *1) Sensitivity Analysis Through NN Statistical*

This tool is working on the principle of shifting the values of input slightly and recording the corresponding change in output, then reporting this change with reference to standard deviation. By default, the first input is varied between its mean

TABLE 3: Best ANN model statistical results for the model testing step.

| Performance | Total fuel demand | Exhaust temperature | VIGV actual position | IP compressor discharge pressure | HP compressor discharge pressure | Exhaust pressure |
|---|---|---|---|---|---|---|
| MSE | 874.13 | 15.030 | 1.4053 | 0.0488 | 0.1081 | 0.0164 |
| NRMSE | 0.0256 | 0.0583 | 0.0486 | 0.0264 | 0.0124 | 0.0129 |
| MAE | 630.57 | 8.1138 | 0.9101 | 0.0319 | 0.0587 | 0.0087 |
| NAME | 0.0185 | 0.0314 | 0.0314 | 0.0173 | 0.0067 | 0.0068 |
| Min Abs. Err. | 11.480 | 0.0195 | 0.0014 | 0.0003 | 0.0027 | 6.1E-06 |
| Max Abs. Err. | 4046.3 | 61.094 | 4.6115 | 0.1825 | 0.9157 | 0.1316 |
| β | 0.9630 | 0.8098 | 0.9337 | 0.9349 | 0.9875 | 0.9877 |
| Score | 95.865 | 87.137 | 93.577 | 94.446 | 97.794 | 97.779 |

(±) and a user-defined number (i.e. 0.1) about the mean value while all other inputs are fixed at their respective means, and then the corresponding deviation in outputs is calculated. Table 4 shows the sensitivity statistics of all outputs due to all inputs produced by the ANN model.

The result in Table 4 shows that the sensitivity of all outputs to generator active power is the highest, where the numbers show higher values of the standard deviation. Similarly, the sensitivity of all outputs to ambient air pressure comes second, and then the sensitivity of all outputs to ambient air temperature and ambient air humidity comes last.

TABLE 4: SENSITIVITY ANALYSIS THROUGH NN SOFTWARE, STANDARD DEVIATION VALUES.

| Sensitivity Parameter | Fuel demand | Exhaust temperature | VIGV actual position | IP compressor discharge pressure | HP compressor discharge pressure | Exhaust pressure |
|---|---|---|---|---|---|---|
| Ambient air temp. (0c) | 300.567 | 9.62160 | 0.2082 | 0.0151 | 0.0765 | 0.0104 |
| Ambient air pressure (bar) | 1210.12 | 35.6710 | 0.4688 | 0.0420 | 0.0620 | 0.0561 |
| Ambient air humidity (%) | 80.1191 | 4.95960 | 0.2737 | 0.0019 | 0.0048 | 0.0010 |
| Generator active power (kW) | 5378.39 | 31.7449 | 7.9985 | 0.3466 | 1.4921 | 0.2277 |

TABLE 5: SENSITIVITY ANALYSIS BY EXCLUDING INPUTS, ERROR DIFFERENCE % AVERAGE.

| Excluded Input | Fuel Demand | Exhaust Temperature | VIGV Actual Position | IP Compressor Discharge Pressure | HP Compressor Discharge pressure | Exhaust Pressure |
|---|---|---|---|---|---|---|
| Ambient Air Temp. (0c) | 0.467912 | 0.714733 | 0.879418 | 0.251124 | 0.300128 | 0.373305 |
| Ambient Air Pressure (bar) | 0.447455 | 0.647371 | 1.000381 | 0.252298 | 0.235971 | 0.305363 |
| Ambient Air Humidity (%) | 0.454350 | 0.479682 | 0.979013 | 0.325943 | 0.149498 | 0.226615 |
| Generator Active Power (kW) | 1.286848 | 0.640851 | 3.570723 | 0.669770 | 0.899850 | 0.945075 |

*2) Tool Sensitivity analysis by excluding inputs*

This test provides a logical analysis of input influence on outputs, if one input is removed then a model is constructed using the rest of the inputs. The significance of this removed input will be reflected in error values generated at the output. The larger the error, the bigger the influence of this input and vice versa. In this part, five models are to be constructed.

One model, the reference model, is constructed with all inputs included. The other four models were constructed with one input removed at a time to represent the effect of excluding one of the original four inputs. The resulting predictions of each model are compared to actual measurements to find the corresponding error. Then the errors will be compared with reference model errors. Thus, one can determine which parameter has the biggest impact on output variables, Table 5.

*C. GT Performance Prediction*

GT first-year operational data was used to study the ability of the MLP-NN model to predict GT performance. Statistical results for the best MLP model prediction errors are presented in Table 6. Also, the predicted values by the ANN model, actual values and prediction error of different parameters are shown in Fig. 4.

It can be seen from both Table 6 and Figure 4, that the predicted fuel demand is very close to the actual fuel demand where the average error percentage was about 0.6%. Similarly, all other parameters show relatively small values of the percentage error ranging between (0.2-0.6 %), while the highest error value was 1.2 % for the VIGV position. The average error percentages from this model are acceptable for all parameters (less than unity), even though still slightly high for Valve Inlet Guide Vanes (VIGV).

TABLE 6: MLP PREDICTION ERRORS.

| | Error % | | | | | |
|---|---|---|---|---|---|---|
| | Fuel demand | Exhaust temperature | VIGV actual position | IP compressor discharge pressure | HP compressor discharge pressure | Exhaust pressure |
| Max. | 8.5 | 7.4 | 23.2 | 8.2 | 3.6 | 5.1 |
| Min. | 1.4E-07 | 2.0E-4 | 1.0E-3 | 5.0E-4 | 4.0E-4 | 2.0E-4 |
| Average | 0.6 | 0.5 | 1.2 | 0.4 | 0.2 | 0.3 |

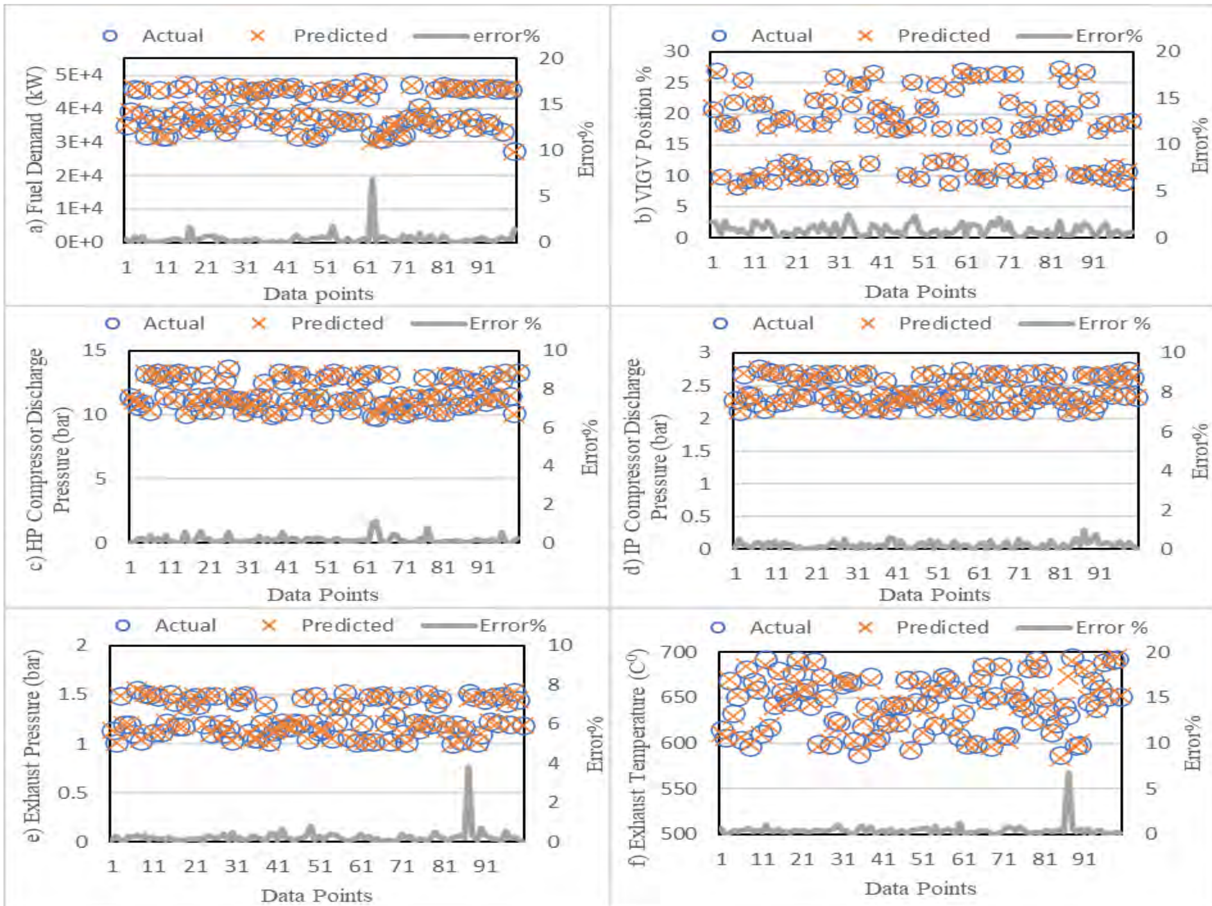


Fig. 4. MLP NN model Prediction VS actual results for a) Fuel Demand (kW), b)VIGV Position, c)HP Discharge Pressure, d)IP Discharge Pressure, e)Exhaust Pressure, and Exhaust Temperature.

Therefore, the analytical values presented show the ability of MLP prediction for all output data, although some points show bigger deviations, on average, all values were small.

## D. *GT Degradation*

GT second-year operational data was used to study the prediction of system degradation that happened due to different operating conditions.

This study is an overall prediction of the whole system and does not study specific component deterioration. The principle is to feed the data of the second year into the model constructed with data of a healthy first year for prediction. This model is used as a reference to the system's normal healthy performance. The calculated percentage errors are due to the difference between the healthy data and operational data of the second year, as shown in Table 7.

TABLE 7: RB211-24G DEGRADATION PREDICTION, THROUGH COMPARISON OF AVERAGE MSE[%] RESULTS FROM MLP NN MODEL FOR THE FIRST AND SECOND YEAR.

| Fuel demand | Exhaust temperature | VIGV actual position | IP compressor discharge pressure | HP compressor discharge pressure | Exhaust pressure |
|---|---|---|---|---|---|
| | | | After the first year | | |
| 0.5518 | 0.5491 | 1.2056 | 0.3714 | 0.1735 | 0.3185 |
| | | | 1st Half of the second year | | |
| 0.4622 | 0.5413 | 2.1690 | 0.7437 | 0.6418 | 0.4278 |
| | | | 2nd Half of the second year | | |
| 0.5686 | 0.7073 | 3.1171 | 0.7828 | 0.6783 | 0.4510 |

Table 7 shows a comparison between error percentages that occurred from the model based on the first-year and second-year data separately. Second-year data was divided into two halves, first and second, thus degradation can be better illustrated.

The results from Table 7 show a slight difference in general, although it shows almost double the value or more for IP compressor discharge pressure and six times HP compressor discharge pressure compared to the health values in the first year. Hence, a possible explanation for these values could be the presence of compressor fouling and this could lead to deciding on compressor wash to reduce this deviation. representation of the error difference between actual and predicted results for three parameters namely, fuel demand IP and HP compressor pressure are shown in Figure 5.

In Figure 5a the graph shows fuel demand actual and predicted values of the second year against Power. It is shown that values are good within the error shown in Table 7. Similarly, Figure 5b represents IP compressor discharge pressure, actual and predicted values of the second year against Power. It is shown that the IP compressor discharge pressure is overpredicted explaining the large errors, In Figure 5c Hp compressor discharge pressure, actual and predicted values of the second year against Power are presented. It is shown that the HP compressor discharge pressure is overpredicted explaining the large errors shown in Table 7.

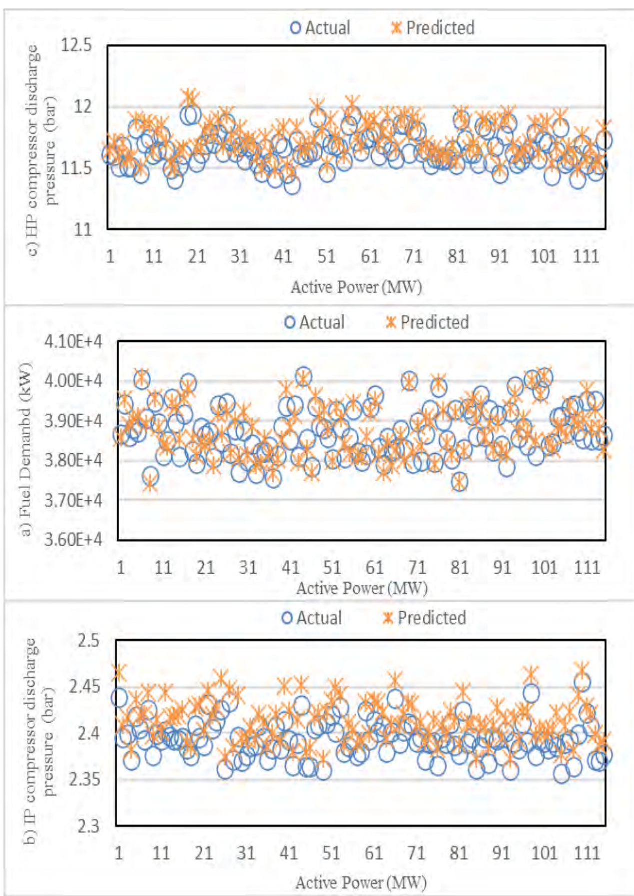


Fig. 5. Degradation Study, a) Fuel Demand [kW], b) IP compressor discharge pressure [bar] and c) HP compressor discharge pressure [bar].

## IV. Conclusion

This research was mainly dedicated to achieving two objectives. First, presents a development study that concerns the optimization of the ANN-based model to be used in GT performance prediction. Second, investigate the proposed model for performance predictability. The prediction ability of the optimised ANN-based model proved to be reliable and convenient for all studied parameters. Different statistical values were introduced and almost all results were promising and convenient. Also predicted results showed a high correlation with the actual measurements.

Sensitivity analysis was introduced to measure the importance of different inputs to the desired outputs. This way, the results give an indication of which parameter is effective and which one is less. Also, this showed that other parameters could be involved in construction if available for better prediction capability. Then a degradation study of GT was introduced using data from the first and second GT's operation years. Results of the second-year prediction show little deviation from that of the first which is considered a healthy condition reference. It was mostly the compressor side that showed noticeable change. This could be due to compressor fouling for which compressor washing could be advised, or for any other possible reasons such as clogged filters.


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