Estimation of APU Failure Parameters Employing Linear Regression and Neural Networks

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ABSTRACT

This study is concerned with the building of an appropriate model to estimate failure parameters of an Auxiliary Power Unit (APU). Linear and nonlinear models were used in order to evaluate which model is more suitable for this application. Data for model building and testing were obtained by simulating a nonlinear dynamic model of APU in Matlab/Simulink for various operating conditions to which it may be subjected to and with different levels of failure parameter degradation. Linear models were obtained by least-squares regression, whereas nonlinear models were obtained by training neural networks. The results obtained with these two models were compared. As a result, the neural network models were found to provide a better estimate of the APU failure parameters.

1. INTRODUCTION

The aviation business has grown rapidly in the last decade and the competition between operators becomes increasingly fierce. The development of new technologies to reduce costs and maximize operating profit has become the goal of the manufacturers in order to produce aircraft with competitive advantage. For this purpose, the increase in aircraft availability by means of improved maintenance techniques has become a key issue.

Nowadays aircraft maintenance is no longer a procedure merely reactive (conducted after the occurrence of a fault). Instead, it includes preventive actions (taken to avoid the occurrence of faults and based on statistics of mean time to failure of components) and tends to include more and more predictive actions (Vieira, 2008). In this last case, parameters are used to indicate the condition or state in which a system is close to the end of its useful life.

Hence concerns about systems Prognostics and Health Management (PHM) have increased among aircraft manufacturers. PHM covers the use of various techniques to evaluate the degradation state of a system through operational data analysis. Health data analysis enables optimization of maintenance activities, which reduces aircraft operational and maintenance costs and increases aircraft availability, therefore increases the operating profit of the airline.

In order to implement PHM in a system it is useful to have reasonable and representative amount of measured parameters of this system or other systems that are affected by it. However, the addition of new sensors could result in increasing costs for the manufacturer and add aircraft weight. It could also increase maintenance costs, since the number of components that might fail and require replacement would be higher.

As the aircraft operate under varying conditions of temperature, pressure and load, it is important that the PHM of an aviation system takes into account different operating conditions to which the system is subjected in order to avoid that the effects of variations in operating conditions are interpreted as system degradation.

This paper aims to determine an appropriate method to estimate values of failure parameters introduced in a nonlinear dynamic model of APU. Due to the simplicity of implementation, the linear approach was tried first. Since the results obtained from the use of linear regression did not get an acceptable accuracy, neural networks implementation was chosen in an attempt to get better results. Several levels of degradation of failure parameters are considered, as well as various operating conditions to which an APU is subjected.

The remainder of the text is organized as follows. Section 2 contains a brief description of an APU system, as well as the adopted model and the values of operating conditions and failure parameters that were used in this study. Section 3 presents the methods used to estimate failure parameters and the methodology adopted. Section 4 discusses the estimation results. Concluding remarks are presented in Section 5.

2. AUXILIARY POWER UNIT

The aircraft APU is a gas turbine whose main function is to assist with starting of the engines. In addition it is capable to provide pneumatic power to other systems, as well as electrical power through the activation of an electrical generator. In principle the APU is intended to operate on the ground, but it can be used in an emergency to run the generators in flight.

A typical APU is composed of three main elements which are compressor, combustor and turbine. It also has auxiliary components: fuel system, bleed system that controls the amount of extracted pneumatic power, gearbox and electrical generator. Control laws of the APU are performed by the Full Authority Digital Engine Control (FADEC) (Vianna *et al.*, 2011). An APU schematic diagram is presented in Figure 1.

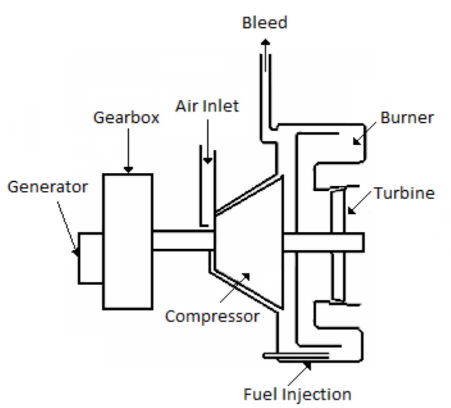

Figure 1. APU schematic diagram.

In order to provide information to FADEC, the APU has several sensors that measure shaft speed, exhaust gas temperature (EGT), bleed pressure and fuel flow.

2.1. APU Model description

The thermodynamic model of APU used in this work was developed in MATLAB/Simulink. The model consists of blocks that model the behavior of each physical component of a real APU. A schematic representation of this model incorporating blocks of three major components, compressor, combustor and turbine, plus two others that model the dynamic of the shaft and the control system is shown in Figure 2. The APU model used in this work is owned by Embraer and content rights are owned by the supplier. Then details about equations and methods related to model construction and faults modeling cannot be shown in this paper.

The three model outputs (EGT, bleed pressure and fuel flow) correspond to sensed values of a real system. The model has inputs for environmental conditions, temperature and pressure, which influence the system behavior. It also has an input for bleed flow and, internally to compressor block, there is an input for shaft power representing the power extracted by the electrical generator.

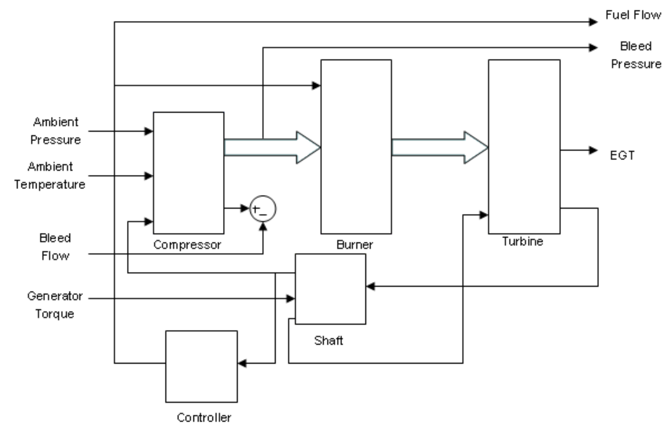

Figure 2. APU model block diagram.

In a real APU, the compressor is the unit that provides compressed air to the combustor. Its performance is defined by parameters such as pressure ratio (ratio between the output pressure and inlet pressure), air flow rate and total adiabatic efficiency, which represents the degree of deviation of the actual compression process in the compressor from a reversible adiabatic compression process.

The compressor block of APU model has functions implemented using maps obtained from charts similar to those shown in Figure 3. These functions take input parameters such as ambient pressure, ambient temperature and shaft speed to provide torque for the compressor, air flow, pressure and temperature at the compressor outlet as outputs.

The functions implemented in the burner block receive the values of pressure, temperature and flow rate of the input air from the compressor block and the fuel flow rate from the controller, and calculate the combustor outlet pressure, temperature and flow rate. The fuel-air ratio (FAR) is also an output of this block.

The turbine block has functions based on maps obtained from charts similar to those shown in Figure 4. These functions take as inputs shaft speed and the corrected value of the air flow, and provide as outputs the pressure ratio, the torque of the turbine and the exhaust gas temperature.

The block that models the control system consists of a PID (proportional-integral-derivative) controller which controls the shaft speed by measuring the APU fuel flow. The block modeling shaft dynamic calculates the resulting shaft acceleration. The value of this acceleration, which depends on the value of inertia of the shaft, is integrated over time to obtain the shaft speed that is the output of this block.

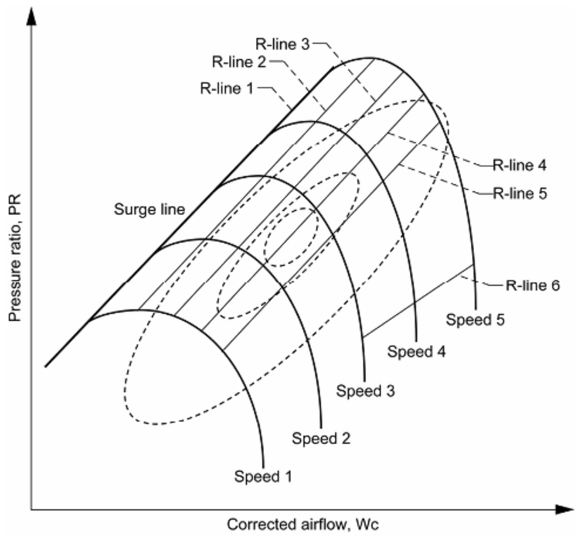

Figure 3. Notional Pressure Ratio Compressor Map (Jones, 2003).

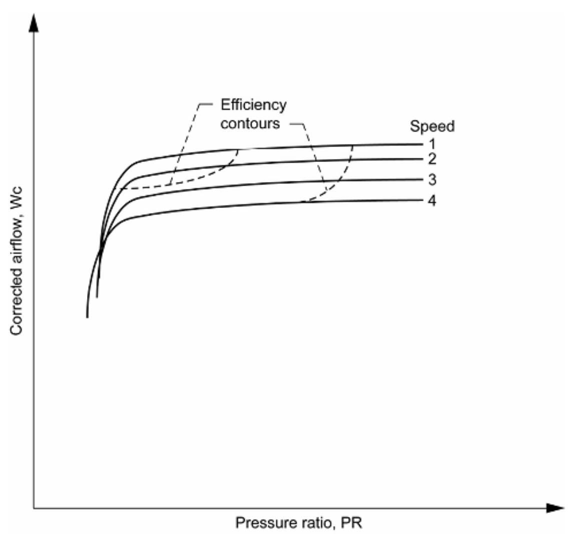

Figure 4. Notional Pressure Ratio Turbine Map (Jones, 2003).

2.2. APU failure parameters

Since an APU is a complex machine made up of several components, various failure modes can occur throughout its life cycle. This work intends to estimate the following three APU failure parameters:

1. Excessive bleed;
2. Compressor efficiency loss;
3. Turbine efficiency loss.

The choice of these failure parameters was based on the fact that their occurrences are commonplace in real APU systems.

2.3. APU Model data acquisition

Operating conditions have a direct influence on the outputs of the APU model. So they must be taken into account in the identification of fault conditions for a satisfactory APU health monitoring. Thus, data for implementing the methods to estimate the failure parameters were obtained through model simulations considering variations in operating conditions and in the degradation of failure parameters with the values specified in Table 1 and Table 2. These values are based on authors' field experience and they cover typical ranges.

Table 1. Values of operating conditions.

Operating Condition	Values
Ambient temperature (ºC)	0, 20 and 40
Ambient pressure (kPa) at sea level, 5000ft and 10000ft	101.35, 85.81 and 70.26
Shaft power required (kJ/s)	0, 22.37, 44.74 and 67.11
Bleed flow extracted (kg/s)	0, 0.189, 0.378 and 0.605

Table 2. Values of failure parameters degradation.

Failure Parameter	Values
Excessive Bleed (kg/s)	0, 0.189, 0.378 and 0.605
Compressor efficiency loss (%)	0, 1.4, 2.8, 4.2, 5.6, 7, 8.4, 9.8, 11.2, 12.6 and 14
Turbine efficiency loss (%)	0, 0.6, 1.2, 1.8, 2.4, 3, 3.6, 4.2, 4.8, 5.4 and 6

To acquire data for estimation model building and testing, three situations were considered. In all situations the operating conditions assume all the possible values from Table 1. These are the situations:

1. The only introduced failure parameter is compressor efficiency loss, which assumes all the possible values of Table 2. Other failure parameters are zero;

2. The only introduced failure parameter is turbine efficiency loss, which assumes all the possible values of Table 2. Other failure parameters are zero;
3. The only introduced failure parameter is excessive bleed, which assumes all the possible values of Table 2. Other failure parameters are zero.

In order to validate the methods, the operating condition values were chosen randomly and limited by their minimum and maximum values on Table 1. Failure parameters were also chosen randomly inside the range described above. For example, in situation 1, compressor efficiency loss values were chosen randomly between 0 and 14%, and the other failure parameters were zero.

3. METHODOLOGY OF FAILURE PARAMETERS ESTIMATION

Sections 3.1 and 3.2 describe the methods employed in this work to build linear and nonlinear models, respectively. Section 3.3 summarizes the methodology for failure parameter estimation.

3.1. Multivariable Linear Regression

Let n be the total number of observations, m the number of explanatory variables (ambient temperature, ambient pressure, shaft power required, bleed flow extracted, EGT, bleed pressure and fuel flow in this work) and z the number of dependent variables (compressor efficiency loss, turbine efficiency loss and excessive bleed in this work) in the regression procedure. The matrix of explanatory variables x_{ij} ($i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$; with an extra column of unit values to account for the offset term in the regression) is denoted by $\boldsymbol{X}$, the matrix of dependent variables y_{ik} ($i = 1, 2, \dots, n$, $k = 1, 2, \dots, z$) is denoted by $\boldsymbol{Y}$, the matrix of linear regression parameters to be estimated b_{lk} ($l = 1, 2, \dots, m$, $k = 1, 2, \dots, z$) is denoted by $\boldsymbol{B}$ and the matrix of values estimated by the method $\hat{y}_{ik}$ ($i = 1, 2, \dots, n$, $k = 1, 2, \dots, z$) is denoted by $\hat{\boldsymbol{Y}}$. These matrices can be arranged in the following format for use in multivariable linear regression:

$$\boldsymbol{Y} = \begin{bmatrix} \hat{y}_{11} & \hat{y}_{12} & \cdots & \hat{y}_{1z} \\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \hat{y}_{2z} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}_{n1} & \hat{y}_{n2} & \cdots & \hat{y}_{nz} \end{bmatrix} \boldsymbol{B} = \begin{bmatrix} b_{01} & b_{02} & \cdots & b_{0z} \\ b_{11} & b_{12} & \cdots & b_{1z} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mz} \end{bmatrix}$$
$$\boldsymbol{X} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1m} \\ 1 & x_{21} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{nm} \end{bmatrix} \hat{\boldsymbol{Y}} = \begin{bmatrix} \hat{y}_{11} & \hat{y}_{12} & \cdots & \hat{y}_{1z} \\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \hat{y}_{2z} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}_{n1} & \hat{y}_{n2} & \cdots & \hat{y}_{nz} \end{bmatrix} \tag{1}$$

By using least-squares, the matrix of linear regression parameters to be estimated, $\boldsymbol{B}$, and the matrix of values estimated by the method, $\hat{\boldsymbol{Y}}$**,** are obtained from

$$\boldsymbol{B} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{Y} \tag{2}$$

$$\hat{\boldsymbol{Y}} = \boldsymbol{X}\boldsymbol{B} \tag{3}$$

In this work one set of the data simulated by the model as described on section 2.3 will be used to obtain B (training set) and the other set will be used to estimate failure parameters $\hat{Y}$ (test set). As a measure of estimation performance, the mean square error (MSE) between estimated and true values will be calculated for the pth failure parameter as

$$MSE(p) = \frac{\sum_{i=1}^{n}\left(y(i,p) - \boldsymbol{Y}(i,p)\right)^2}{n}, p = 1, \dots, z \tag{4}$$

3.2. Neural Networks

Artificial neural networks (ANNs) have been widely investigated for use in fault diagnosis. ANNs are trained to map inputs to outputs via nonlinear relationships in an architecture which resembles the process performed in the brain. Generally, the neural network operates in two phases: one learning phase and one operation phase. The purpose of the learning phase is to adjust the parameters of the neural network which will allow the neural network to function properly during the operation phase (Marinai, 2004).

In this work, Multi Layer Perceptron (MLP) networks with sigmoidal activation function are employed (Marinai, 2004). The adopted MLP architecture comprises three layers: input layer, hidden layer and output layer. Training is accomplished by using the well-known backpropagation algorithm, as implemented in the Neural Network Toolbox of MATLAB (version R2010a). The network inputs and outputs were defined as in the linear regression case.

3.3. Methodology for failure parameters estimation

The flowchart in Figure 5 summarizes the methodology employed in this study. It is worth noting that the data resulting from the APU simulations were divided into two separate sets for model building and validation purposes.

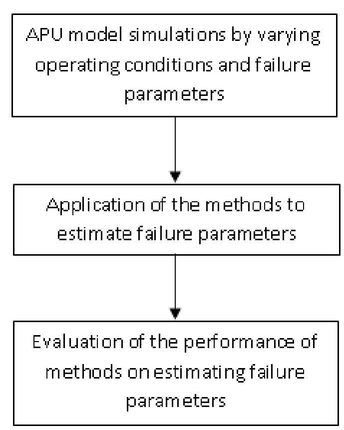

Figure 5. Methodology for evaluating the performance of the estimation methods.

4. RESULTS

4.1. Linear Regression

4.1.1. Situation 1

The MSE between the values of compressor efficiency loss estimated by linear regression and the values that were indeed used on simulation was 2.9×10^{-4}. The estimation results are depicted in the plot of estimated *versus* true values presented in Figure 6. The line in the plot represents the optimal result that would be obtained if estimated value was equal to true value.

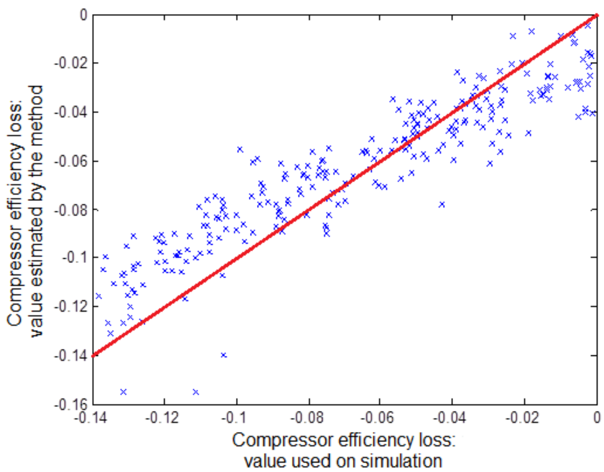

Figure 6. Compressor efficiency loss values from simulation versus values estimated by the linear regression model.

4.1.2. Situation 2

The MSE for estimation of turbine efficiency loss by the Least Squares Method was 6.9×10^{-5}. Figure 7 shows the plot of the values of simulation against the estimated values.

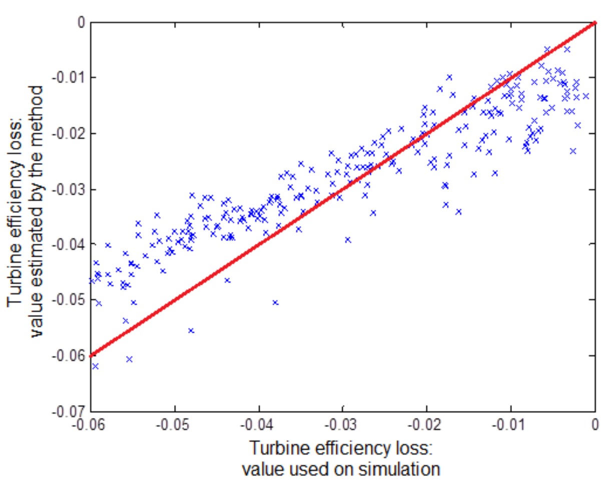

Figure 7. Turbine efficiency loss values from simulation versus values estimated by the linear regression model.

4.1.3. Situation 3

The MSE for estimation of excessive bleed by the Least Squares Method was 136. Figure 8 shows the plot of the values of simulation against the estimated values.

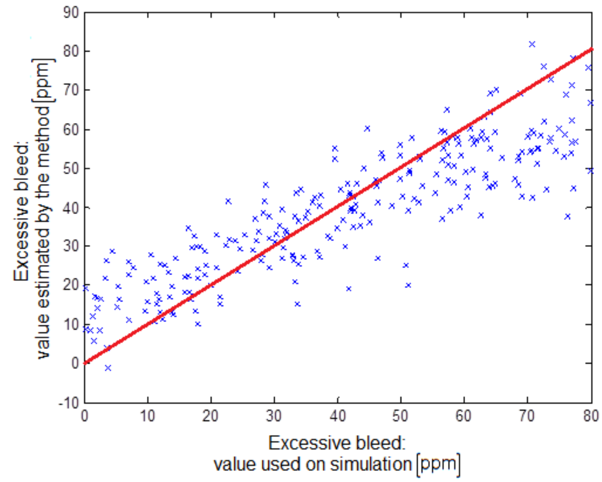

Figure 8. Excessive bleed values from simulation versus values estimated by the linear regression model.

4.2. Neural Networks

4.2.1. Situation 1

The MSE calculated for estimation of compressor efficiency loss by the neural network was 1.6×10^{-5}. Figure 9 shows the plot of the values of simulation against the estimated values.

By comparing Figure 6 with Figure 9 and the MSE values obtained by linear regression and the neural network, it is possible to notice that the neural network presented better performance on estimating compressor efficiency loss values.

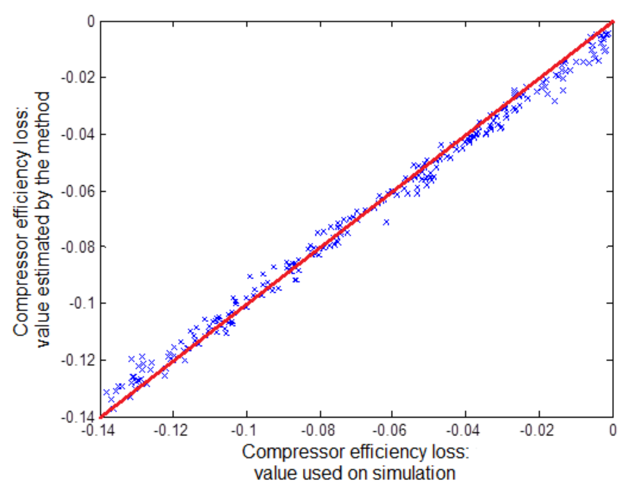

Figure 9. Compressor efficiency loss values from simulation versus values estimated by the neural network model.

4.2.2. Situation 2

The MSE for estimation of turbine efficiency loss by the Neural Network is 1.0×10^{-7}. Figure 10 shows the plot of the values of simulation against the estimated values.

By comparing Figure 7 with Figure 10 and the MSE values obtained by linear regression and the neural network, it is possible to notice that the neural network also presented better performance on estimating turbine efficiency loss values.

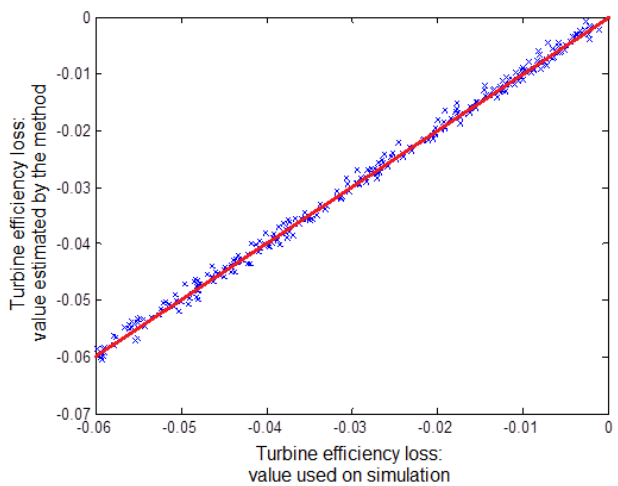

Figure 10. Turbine efficiency loss values from simulation versus values estimated by the neural network model.

4.2.3. Situation 3

The MSE for estimation of excessive bleed by the Neural Network was 1.4. Figure 11 shows the plot of the values of simulation against the estimated values.

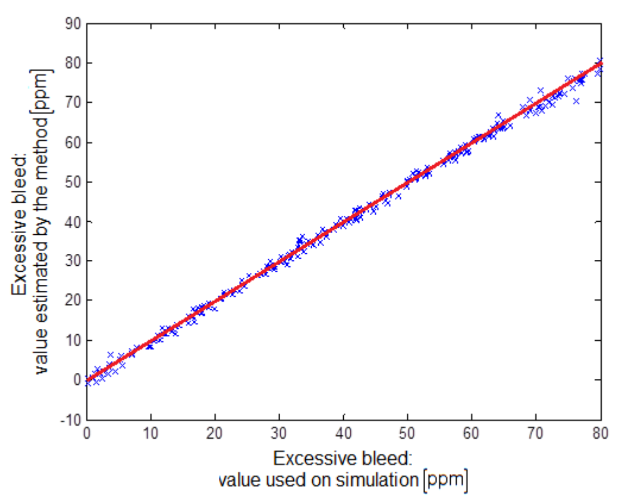

Figure 11. Excessive bleed values from simulation versus values estimated by the neural network model.

By comparing Figure 8 with Figure 11 and the MSE values obtained by linear regression and the neural network, it is possible to notice that the neural network presented better performance on estimating excessive bleed values.

4.3. Results Summary

The MSE for both methods are summarized on the table below:

Table 3. MSE summary.

	Linear Regression	Neural Network
Situation 1	2.9×10^{-4}	1.6×10^{-5}
Situation 2	6.9×10^{-5}	1.0×10^{-7}
Situation 3	136	1.4

5. Conclusion

This paper presented the results of an investigation involving the use of linear regression and neural networks for the estimation of APU failure parameters from operating conditions and measurements of EGT, bleed pressure and fuel flow. In all cases, the neural network models provided considerably better estimation results which indicates that there are nonlinearities in the relation among the monitored variables that cannot be neglected.

Future works could be concerned with extensions of this investigation to encompass the use of field data.

Acknowledgments

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