Health Monitoring of an Auxiliary Power Unit Using a Classification Tree

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ABSTRACT

The objective of this work is to present a method to monitor the health of Auxiliary Power Units (APU) using a Dynamic Computational Model, Gas Path Analysis and Classification and Regression Trees (CART). The main data used to train the CART consists of measurements of the exhaust gas temperature, the bleed pressure and the fuel flow.

The proposed method was tested using actual APU data collected from a prototype aircraft. The method succeeded in classifying several relevant fault conditions. The few misclassification errors were found to be due to the insufficiency of the information content of the measurement data.*

1. INTRODUCTION

Increased aircraft availability is one of the most desirable fleet characteristics to an airliner. Delays due to unanticipated system components failures cause prohibitive expenses, especially when failures occur on sites without proper maintenance staff and equipments. In recent years researches have focused on providing new technologies which could prevent some failures or notify maintenance staff in advance when any component is about to fail. Health Monitoring (HM) provides this knowledge by estimating the current health state of components. This may guide the maintenance activities and spare parts logistics to properly remove or fix the component at the most suitable time and place.

Since the Auxiliary Power Unit (APU) represents a significant maintenance cost to an airliner, several HM studies have been conducted on this component (Vieira et al, 2009; Urban, 1967; Jones, 2007). Many of them exploit similar approaches to methods devoted to the main engines, due to the similarities in physical behavior.

Methods based on thermodynamic models, or gas path analysis, may provide more precise information as compared to data-driven methods. However, the use of model-based techniques still presents challenges when dealing with a large and heterogeneous fleet.

This paper aims to provide a HM solution based on a classification and regression tree (CART) employing data obtained from a mathematical model of an APU derived from thermodynamic principles. The proposed method is validated with APU field data.

The work is organized as follows. Section 2 contains a brief description of the system under analysis. Section 3 presents the methodology adopted. Section 4 contains the model description used on the implementation. Section 5 presents the implementation steps and the results of the method applied on the APU performance data. The last section presents the conclusion of the study and some remarks.

2. SYSTEM DESCRIPTION

An APU is a gas turbine device on a vehicle with the purpose of providing power to other systems apart from engines. This power can either be of pneumatic nature, extracted from a bleed system, or of electrical type, extracted from the generator. APUs are commonly found on large aircraft, as well as some large land vehicles. Its primary purpose is to provide bleed to start the main engines. It is also used to run accessories such as air conditioning and electric pumps. It is usually located at the tail end of the aircraft as represented in Figure 1.

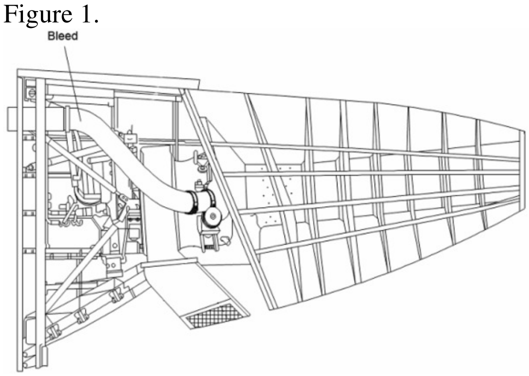

Figure 1: APU at the tail end of an aircraft.

A typical gas turbine APU contains a compressor, a burner and a turbine as every conventional gas turbine. It also has a bleed system that controls the amount of extracted pneumatic power, a fuel system, a gearbox and a generator. Protective components such as anti-surge, and guide vane may also be present. The logics and control are executed by the Full Authority Digital Engine Control (FADEC). A simplified APU representation is illustrated in Figure 2.

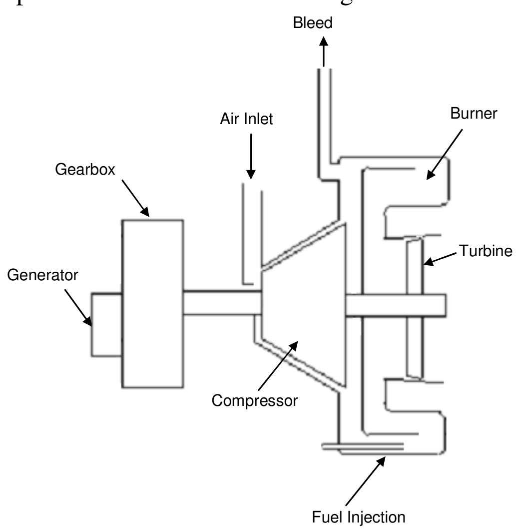

Figure 2: Simplified APU representation.

In order to provide proper information to the FADEC, the system must contain sensors for several variables, such as speed, exhaust gas temperature (EGT) and bleed pressure. A fuel flow meter may also be valuable but it is not an essential sensor. The EGT is a useful parameter for health monitoring and can indicate several failures such as core degradation and inlet blockage (SAE, 2006). A typical EGT profile during APU operation is indicated in Figure 3.

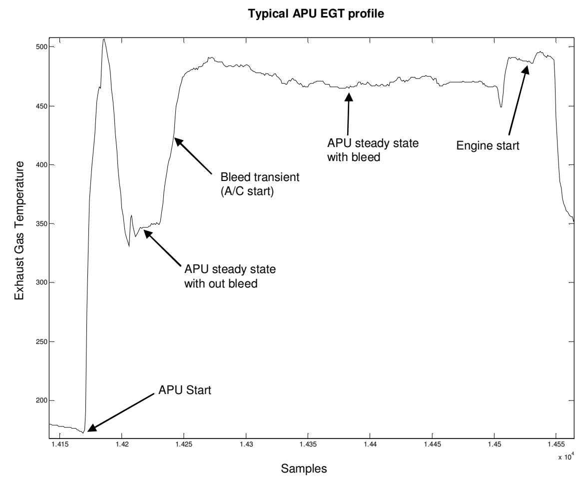

Figure 3: Typical EGT profile during the operation of an APU.

During the APU start an EGT peak is observed and can be used as a health monitoring feature (SAE, 2006). After the speed has reached its operational value the EGT stabilizes until the air conditioning system turns on. This produces an increase in EGT, which then reaches another steady-state value. When the engine starts, usually all other pneumatic sources are turned off so the APU can provide the required bleed.

3. HEALTH MONITORING METHODOLOGY

Gas path analysis is a methodology for monitoring gas turbines proposed by (Urban, 1967), which has been used in several studies for the purpose of health performance analysis (Saravanamuttoo et al, 1986) , (Li, 2003). Within the scope of APU monitoring, one of the main challenges consists of discriminating among possible failure modes affecting different components. In this context, promising results have been obtained with the use of classification methods (Vieira et al, 2009), (Sabyasachi, 2008).

Classification and Regression Trees (CART) are a popular set of classification methods that have as one of its key characteristics the easiness of interpretation of the results. This feature facilitates the validation of the results or the adjustment of the classification rules on the basis of the knowledge of a system specialist.

CART uses a “learning sample” of historical data with assigned classes for building a “decision tree”, which expresses a set of classification rules in terms of a sequence of questions. The use of CART involves three stages (Timofeev, 2004):

1. Construction of the maximum tree
2. Selection of an appropriate tree size
3. Classification of new data using the resulting tree

The classification tree uses some rules to split the “learning sample” into smaller parts, thus creating the nodes and the tree itself. Such rules are called “splitting rules". Some examples are the "Gini splitting rule" and the "Twoing splitting rule". The first one is the most broadly used (Timofeev, 2004) and uses the following "impurity" function:

$$i(t) = \sum_{k \neq l} p(k \mid t) \tag{1}$$

where k and l are class indexes, t is the node under consideration and $p(k|t)$ is the conditional probability of class k provided in node t.

At each node the CART solves a maximization problem of the form:

$$\underset{x_j \le x_j^R,\, j=1,\ldots M}{\arg\max} \left[i(t_p) - P_l i(t_l) - P_r i(t_r) \right] \tag{2}$$

where P_l and P_r are probabilities of the left and right node respectively.

Using the Gini impurity function, the following maximization problem must be solved to isolate the larger class from other data

$$\underset{x_j \le x_j^R,\, j=1,\ldots M}{\arg\max} \left[-\sum_{k=1}^{K} p^2(k \mid t_p) + P_l \sum_{k=1}^{K} p^2(k \mid t_l) + P_r \sum_{k=1}^{K} p^2(k \mid t_r) \right] \tag{3}$$

The health monitoring algorithm proposed in the present work employs CART for failure classification based on residuals from faulty and healthy data in steady state condition. The first implementation step was choosing the failure modes, variables used for model seeded fault, list of sensors and operational data snapshots for analysis.

Eight types of faults were considered:

1. Increase in shaft torque extraction;
2. Increase in bleed;
3. Reduction in compressor efficiency;
4. Reduction in turbine efficiency;
5. Speed sensor bias;
6. EGT sensor bias;
7. Reduction in combustor efficiency;
8. Decrease in fuel flow.

The measured variables were assumed to be fuel flow, EGT and bleed pressure. Healthy data and faulty data were generated using the mathematical model of an APU derived from thermodynamic principles. The residuals used as inputs for CART were calculated as shown in Figure 4.

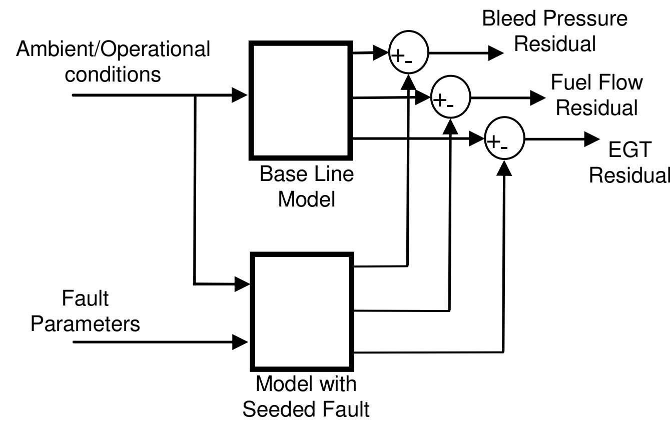

Figure 4: Calculation of the residuals employed in the proposed HM methodology.

4. MODEL DESCRIPTION

The thermodynamic model used in this work is represented schematically in Figure 5.

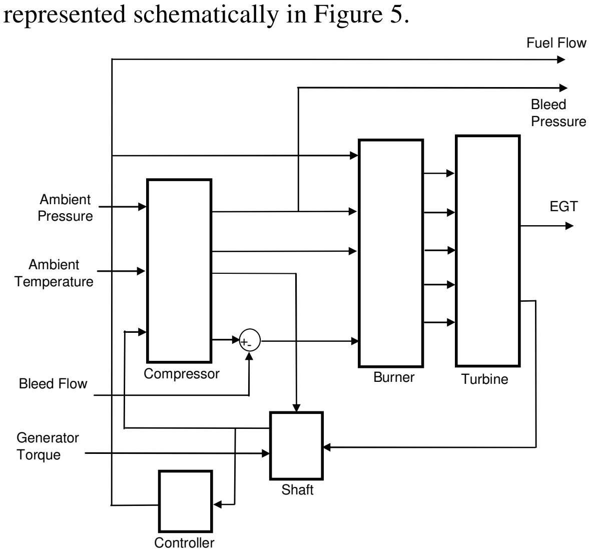

Figure 5: Block diagram of the APU model.

The model contains four inputs and three outputs, which represent the APU sensors. Three of the blocks model the thermodynamic behavior: the compressor, burner and turbine.

The inputs to the compressor block consist of ambient pressure and temperature, as well as shaft speed. The outputs are compressor torque, air flow, compressor pressure and temperature. The compressor behavior is based on a map which relates pressure ratio, airflow, speed and temperature as illustrated in Figure 6.

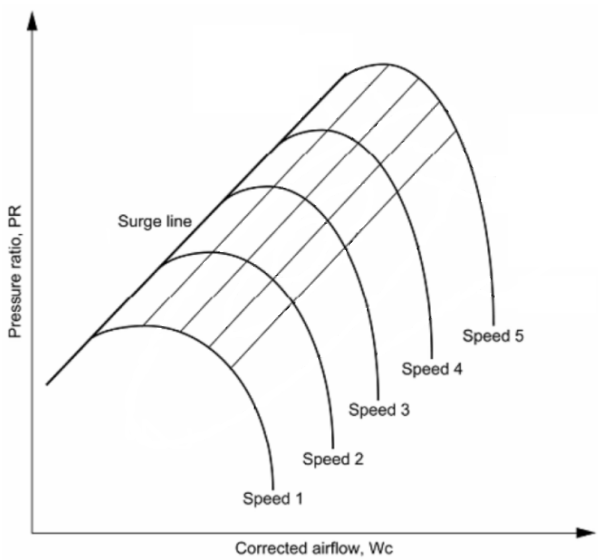

Figure 6: Compressor map.

The pressure ratio (PR) is defined as:

$$PR = \frac{P_{out}}{P_{in}} \tag{4}$$

where P_{out} is the outlet pressure and P_{in} is the inlet pressure.

The corrected air flow is defined as:

$$W_c = W\sqrt{\frac{\theta}{\delta}} \tag{5}$$

where W is the absolute air flow and δ and θ are given by:

$$\delta = \frac{P_{in}}{P_{ref}} \tag{6}$$

$$\theta = \frac{T_{in}}{T_{ref}} \tag{7}$$

where P_{ref} is the standard day pressure, T_{ref} is the standard day temperature and T_{in} is the inlet temperature.

The corrected speed (N_c) is defined as:

$$N_c = \frac{N}{\sqrt{\theta}} \tag{8}$$

where N is the absolute shaft speed.

The inputs to the burner block are air flow, compressor pressure and temperature, as well as fuel flow. The outputs are burner pressure and temperature, air flow and Fuel Air Ratio (FAR). The input-output characteristic of this component is represented as:

$$h_{out} = \frac{W_{air}.h_{in} + LHV.W_{fuel}}{W_{air} + W_{fuel}} \tag{9}$$

where h_{in} and h_{out} are respectively the burner inlet and outlet enthalpies, W_{fuel} is fuel flow, W_{air} is the burner exhaust air flow and LHV is the fuel heating value.

The turbine is represented by a map as illustrated in Figure 7.

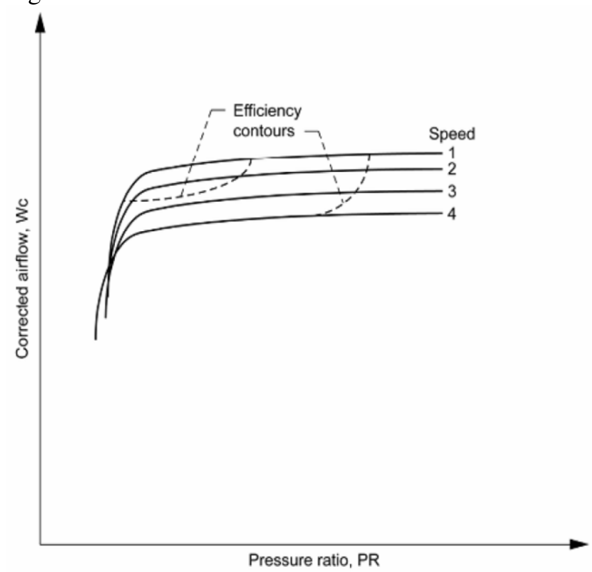

Figure 7: Turbine map.

Apart from the thermodynamic blocks, two other components are modeled in Fig. 5. The first one is the controller, which reproduces one of the main features of the FADEC, namely the control of shaft speed by manipulation of fuel flow. Here, a PID controller is used. The other block represents the energy balance of the shaft speed, which can be described by the following equation:

$$\sum\tau = I.\dot{N} \Rightarrow N = \int \frac{\sum\tau}{I} \tag{10}$$

where I is the moment of inertia and $\Sigma\tau$ is the sum of compressor, turbine and generator torques. The latter represents the torque extracted from the APU to supply electrical components such as electrical pumps and lights.

5. RESULTS

For the construction of the initial classification tree, a set of 180 data vectors was generated. This dataset generation consisted of 20 simulations of APUs startups for each of the failure modes and other 20 simulations for the APU operating without faults. Different loads, simulating pumps, engines and air cycle machine were used.

The data vectors collected comprised residual values of EGT, fuel flow and bleed pressure.

The resulting classification tree is presented in Figure 8.

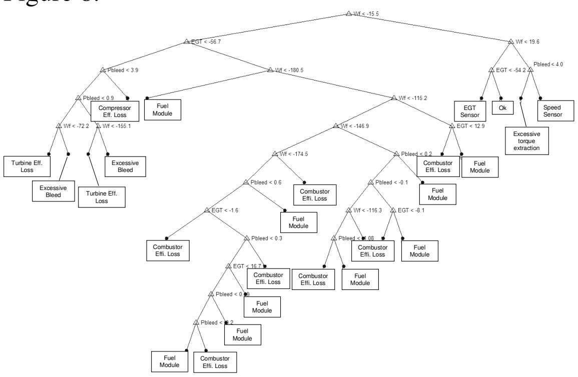

Figure 8: Initial classification tree.

Analyzing the initial classification tree it is possible to notice the great number of nodes possibly resulting in overfitting of the training data. This problem was solved by pruning some nodes of the tree using expert knowledge provided by an APU system specialist. Some of the failure modes were very similar and it would be a better strategy to group them into a reduced number of nodes. The resulting tree is presented in Figure 9.

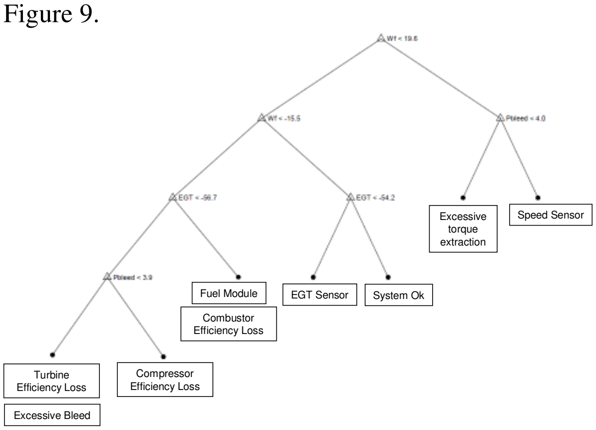

Figure 9: Classification tree resulting from the pruning procedure.

It is possible to observe in Figure 9 that some of the failure modes were grouped into the same node, indicating that they could not be separated based on the sensors that were used. Although the initial objective was to classify all failure modes, some ambiguities could not be resolved. However, the level of isolation provided by the proposed tree was considered adequate, as it helps to reduce significantly the troubleshoot time on an event of failure.

The proposed method was tested using actual data collected in the field. The dataset consisted of 18 data vectors comprising 6 healthy states and 12 failure events. The data were collected with the engine, the electric pump and the air cycle machine in either on or off state, as shown in
Table 1.

Table 1: Field data.

	ACM	Pump	Engine
Healthy	off	off	off
Healthy	off	off	on
Healthy	off	off	on
Healthy	on	on	off
Healthy	on	on	on
Healthy	off	off	on
Excessive Bleed	off	off	off
Excessive Bleed	on	on	off
Excessive Bleed	off	off	off
50% Inlet Blockage	off	off	off
50% Inlet Blockage	on	on	off
50% Inlet Blockage	off	off	off
75% Inlet Blockage	off	off	off
75% Inlet Blockage	on	on	off
75% Inlet Blockage	off	off	off
Fuel Filter Blockage	off	off	off
Fuel Filter Blockage	on	on	off
Fuel Filter Blockage	off	off	off

Although the "Inlet Blockage" was neither modeled nor used for the training of the classification tree, the effects due to this type of failure are very similar to those of an “EGT sensor bias”. Therefore, it is expected that these particular conditions should be classified as “EGT sensor bias” failures.

The results for the classification are presented in Table 2.

Table 2: Classification results for the field data.

Ground Truth	**Classification**
Healthy	No failure
Healthy	No failure
Healthy	No failure
Healthy	No failure
Healthy	No failure
Healthy	No failure
Excessive Bleed	Compressor Eff. loss
Excessive Bleed	Excessive Bleed
Excessive Bleed	Excessive Bleed
50% Inlet Blockage	EGT Sensor
50% Inlet Blockage	EGT Sensor
50% Inlet Blockage	No failure
75% Inlet Blockage	Excessive Bleed
75% Inlet Blockage	Excessive Bleed
75% Inlet Blockage	EGT Sensor
Fuel Filter Blockage	Fuel Module
Fuel Filter Blockage	Fuel Module
Fuel Filter Blockage	No failure

Observing the results presented in Table 2, one can notice that the classification algorithm was able to classify correctly all healthy states, that is, no healthy system was classified as faulty. On the other hand, the algorithm was not able to classify correctly all failure events.

In order to identify possible improvements on the method proposed, all classification errors were analyzed observing the raw data.

Looking at the data from “50% inlet blockage” and “fuel filter blockage” faults, both classified as “no failures”, no significant difference in the parameters were observed, as compared to a situation without fault. The conclusion is that the "Inlet Blockage" and the "Fuel Filter Blockage" were not sufficient to cause any modification on the monitored variables. One factor that could contribute to these errors is the difference in the behavior of the APU in hot and cold starts. This effect was not modeled in the present work.

Lack of precise calibration and modeling data, specifically compressor and turbine maps and lack of precise bleed flow test data lead to errors on “Excessive Bleed” being classified as “compressor efficiency loss” and the “75% Inlet Blockage” classified as “Excessive Bleed”.

6. CONCLUSION

This paper presented an APU health monitoring method using a Dynamic Model and a Classification and Regression Tree (CART). The CART was used to classify APU failure modes based on measurements of the exhaust gas temperature, the bleed pressure and the fuel flow.

After designing the CART, the method was tested using real APU data. Although the method was not capable to classify correctly all failure modes, it showed promising results.

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