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MODEL-BASED DIAGNOSTICS FOR AN AIRCRAFT AUXILIARY POWER UNIT

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Abstract. This paper describes a case study of model-based diagnostics system development for an aircraft Auxiliary Power Unit (APU) turbine system. The off-line diagnostics algorithms described in the paper work with historical data of a flight cycle. The diagnostics algorithms use detailed engine systems models and fault model knowledge available to Honeywell as the engine manufacturer. The developed algorithms provide fault condition estimates that allow for consistent detection of incipient performance faults and abnormal conditions.

1 Introduction

This paper considers diagnostics algorithms and issues for an Auxiliary Power Unit (APU) for aircraft. APU is a small gas turbine engine that provides electrical power and compressed air. Honeywell is the leading manufacturer of airborne APUs. This paper is focused on diagnostics, trending, and prognostics of incipient faults. Such faults often exhibit themselves as a deterioration trend in the turbomachine performance and eventually lead to the need to perform expensive repair and overhaul activities. Timely detection of incipient faults enables preventive maintenance and has significant economic importance. The overall areas of condition monitoring, diagnostics, trending, and prognostics for such faults are known in industry as PTM (Predictive Trend Monitoring).

Accurate and reliable detection and parameter estimation of incipient faults requires detailed and thorough understanding and knowledge of the equipment. Such understanding is available to Honeywell as a turbine engine manufacturer in the form of detailed design and control analysis models. This paper describes diagnostics algorithms based on such detailed models of the engine performance and dynamics. Such approaches have been discussed in the recent literature [1—3], but with more basic models used.

Development of diagnostics algorithms for small turbomachines, such as APUs, has different requirements compared to the bigger turbomachines. The design and development requirements for Auxiliary Power Units have for many years emphasized the reduction of APU system cost and weight. On aircraft installations, available APU sensors are limited to ones essential for the control and safe operation of the turbomachine. Reducing number of sensors is considered to improve the system reliability. Data acquisition systems on aircraft are generally limited by the aircraft data bus and data storage capacity and only a limited amount of APU data can be stored during a flight cycle for subsequent condition monitoring use.

The PTM algorithms discussed in this paper are executed on ground-based host servers between the flight operations. These algorithms process data stored on the aircraft during each flight cycle to recommend a maintenance action. The PTM system design requirements have also to address the preventive maintenance needs for legacy units. For such matured installations, the available flight data are often constrained to snapshots of safety critical APU

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parameters such as speed, Exhaust Gas Temperature (EGT), Load Compressor Inlet Temperature, as well as discrete aircraft commands such as APU Start/Stop command and Main Engine Start command.

A basic approach to PTM is by using snapshot data of the APU steady state performance. Such an approach using the performance models is considered in Section 3 of this paper.

Section 4 considers diagnostics and trending based on the snapshot data of the APU start. During APU starting, a broad envelope of the APU component operation is covered, leading to potentially improved fault observability. At the same time, APU start diagnostics requires using more detailed dynamical models.

Finally, Section 5 discusses even more comprehensive algorithms that can be used if the data are collected at a high rate through the APU start. These algorithms enable a detailed and accurate diagnostics of the engine faults.

2 Technical problem

An auxiliary power unit (APU) is small gas turbine engine that provides pneumatic and electrical power to the airplane. This power is used to start the main propulsion engines, provide pressurized air for aircraft environmental control systems, provide electrical power for aircraft lighting, avionics and galleys on the ground, and to provide backup and emergency power in flight. A cross section of a typical APU is provided in Figure 1.

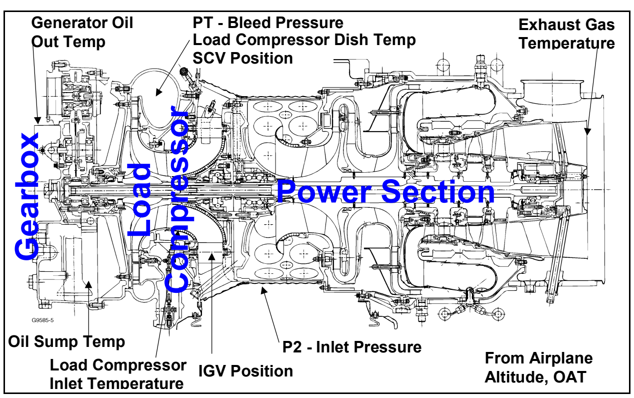

Figure 1. Gas Turbine APU Cross Section.

A typical APU for commercial transport aircraft is broken up into three main sections – the power section, the load compressor and the gearbox. The power section is the gas generator portion of the engine and produces all the power for the APU. The load compressor is generally a shaft-mounted compressor that provides all pneumatic power for the aircraft. There are two actuated devices, the inlet guide vanes that regulate airflow to the load compressor and the surge control valve that maintains stable or surge-free operation of the turbomachine. The third section of the engine is the gearbox. The gearbox transfers power from the main shaft of the engine to an oil-cooled generator for electrical power. Within the gearbox, power is also transferred to engine accessories such as the fuel control unit, the lube module, and cooling fan. In addition, there is also a starter motor connected through the geartrain to perform the starting function of the APU.

A typical federated aircraft control architecture consists of individual subsystem controllers that provide information to a central maintenance unit or central flight data system. Data available for Predictive Trend Monitoring are stored on the central maintenance computer. The stored data is transferred to the ground-based systems after a flight.

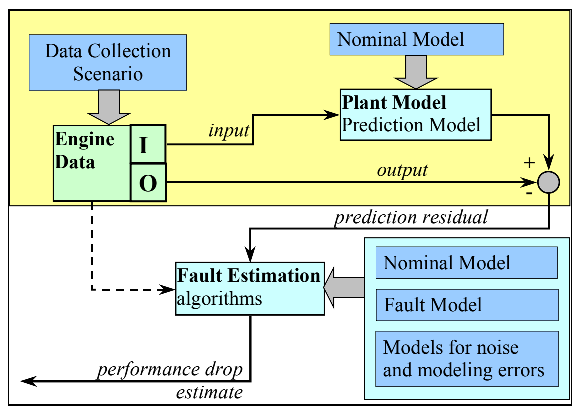

Figure 2. Model-based diagnostics approach

The sensors set on existing APUs are often different for each application. The sensors are commonly selected based on the control system requirements and not for potential health monitoring benefits. A typical suite of sensors is illustrated in Figure 1. The health monitoring and diagnostics algorithms thus have to work with very sparse data. Sensor data availability improves for recently developed or future systems as the technology matures. Much less data is available on the legacy units that need however to be serviced.

By using detailed physical models of the hardware available to the manufacturer it is possible to make an optimal use of the available engine operation data. Such model-based diagnostics approach is considered in this paper and is illustrated in Figure 2. The models include engine models and incipient fault (deterioration) models. Model based diagnostics also require taking into account model inaccuracies and errors, such as parameter variations in time, variation from engine to engine, and sensor noise.

3 APU Steady State Performance

A PTM approach applicable to most APUs with relative ease involves trending performance data to determine the health of the APU in consistent and repeatable conditions. As stated earlier, the APU performs a variety of functions on the airplane, however, many of these functions offer a significant amount of variability depending on the how the other airplane systems are operating. For example, the environmental control system is a complex system of many valves and pieces of turbomachinery that result in different varying load conditions to the APU. As a result, APU health monitoring is performed during main engine starting operation (MES) when variability is reduced with the APU supplying compressed air for starting the main propulsion engine of the aircraft only. The state of the APU during MES is relatively simple and operating condition has good repeatability.

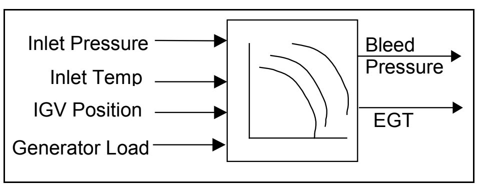

Figure 3. APU steady state performance model

Figure 3 illustrates a performance model used for the diagnostics of the APU from the steady state MES data. The model in Figure 3 is obtained by combining the performance maps of the load compressor and engine power section. The model can be represented as

$$\hat{y} = F(V), \tag{1}$$

where V is the vector collecting the input data for the performance calculations and $\hat{y}$ is the vector collecting the performance predictions. For the Figure 3 model, these vectors have the form.

$$\hat{y} = \begin{bmatrix} \text{Bleed Pressure} \\ \text{EGT} \end{bmatrix}, \qquad V = \begin{bmatrix} \text{Inlet pressure} \\ \text{Inlet temperature} \\ \text{IGV position} \\ \text{Generator Load} \end{bmatrix}$$

Comparing discrete data collected on the APU against the outputs of the simplified APU performance model (2) accounts for much of the variation in the operating conditions. The prediction residuals relate to the performance of power section (EGT) and the load compressor (Bleed Pressure). Computed at the usage cycle n, these residuals have the form.

$$r_n = y_n - \hat{y}_n \tag{2}$$

To detect the APU faults and make the needed maintenance recommendations the residuals are trended. The trending, explicitly or implicitly, uses the following model for the residual evolution

$$r_n = r_0 + s_n + \delta_n,$$

where r_0 is a constant offset of the residual, s_n is the measured parameter change caused by a fault and δ_n is the parameter change caused by the changing ambient conditions and other factors not reflected in the model. The measured parameter change s_n can be distinguished from δ_n by having a different statistical behavior. For instance, δ_n can be assumed to be independent gaussian variables with the same mean and covariance and s_n a step change of an unknown amplitude. The fault-related change of the measured parameter y is estimated from (2) by applying several filtering schemes and heuristics, such as:

a) The residuals are compared to an absolute limit that is based on economics and the requirement for the APU to fulfill its mission. The drift over the limit is illustrated in Figure 4.
b) Sudden change or difference of the residual between successive points.
c) An APU that exhibits a very high rate of the residual change consistently over several cycles is also flagged for removal or inspection.

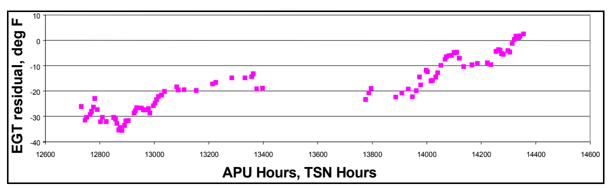

Figure 4. APU steady state performance deterioration

When dealing with on wing data, one must accept and account for additional noise and variation as compared to laboratory test conditions. On wing sensors are designed for robustness and reliability and this results in reduced accuracy. In addition, cross winds across the airplane, air quality, and humidity can significantly impact data repeatability. The timing and sequencing of data acquisition can provide a significant amount of variation especially since nothing on the airplane operates in a pure steady state environment. The processing uses low pass filtered residual data. The filtered trend is compared to the raw data to ensure immediate detection of a sudden change such as a change illustrated in Figure 5.

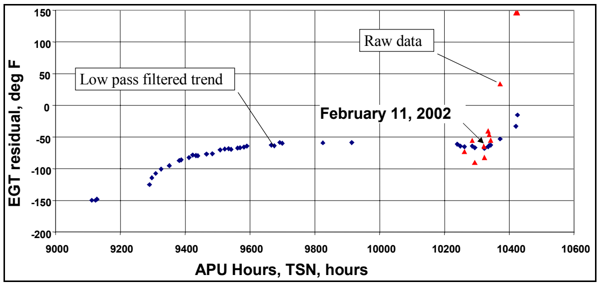

Figure 5. Sudden change in APU performance

4 APU Starting

A more comprehensive analysis of the APU data is required for APU starting. This analysis looks at the snapshot data such as overall start time, peak EGT during start, and the speed at which this peak EGT occurs. Starting of an engine describes its behavior from the moment the START switch is turned on until the engine reaches 95% speed. Although an engine consists of several components, not all of them are important during startup. An integrated model intended for diagnostics during the starting mode involves only those relevant components. These components are shown pictorially in Figure 6.

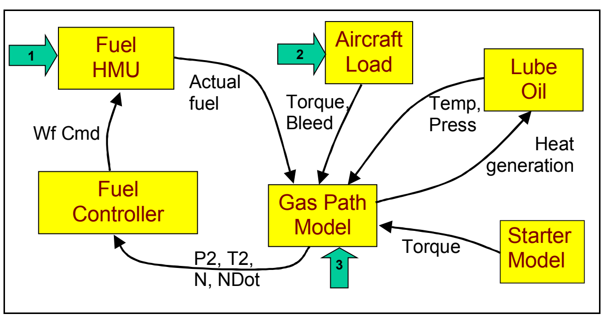

Figure 6. Integrated model of APU starting

As shown in Figure 6, the model consists of the following components:

Gas path. This component captures the torque balance on the engine shaft as the gas flow through the core.

Fuel controller. This component captures the logic associated with the fuel flow command calculations.

Fuel Actuator. This component captures the dynamics associated with the hydromechanical actuation unit that injects fuel into the combustor.

Aircraft. This component captures the inlet and exhaust air duct of the aircraft containing the engine.

Lube Oil. This component captures the heat transfer from the gas path to the lube oil.

Starter. This component captures the torque introduced by an electric starter motor.

In addition to these components, the model also captures the following interactions.

- Heat transfer from the engine core to the lube oil.
- Effect of oil viscosity on parasitic drag on the shaft.
- Effect of engine state on commanded fuel flow.
- Effect of the actual fuel flow on engine core.
- Aircraft duct geometry effect on engine core backpressure.

The model was validated using test cell data for a normal engine. It provides a mechanism for calculating output prediction as described by (1), where the model inputs V and the model prediction outputs $\hat{y}$ are:

$$V = \begin{bmatrix} \text{Ambient pressure} \\ \text{Ambient temperature} \\ \text{Engine altitude} \\ \text{Lube oil temperature} \end{bmatrix}, \ \hat{y} = \begin{bmatrix} \text{Starting time} \\ \text{Max EGT during start} \\ \text{Speed at max EGT} \end{bmatrix} \quad (3)$$

Each prediction of the output requires to complete a simulation run for the APU starting with the ambient and usage parameters V. The simulation run produces predictions $\hat{y}$ of the collected data y.

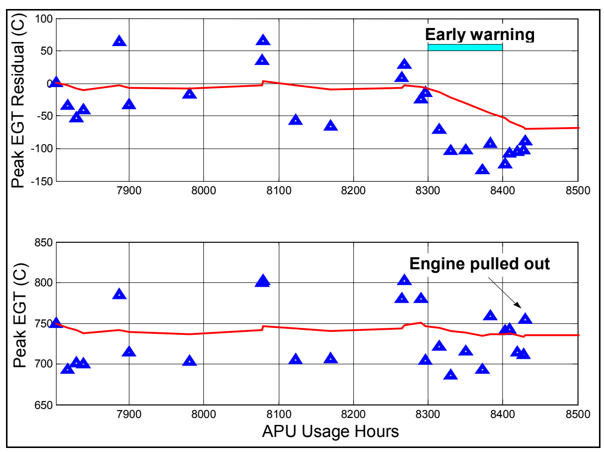

Figure 7. Trending APU starting performance

For each usage cycle data, the predictions $\hat{y}$ and the actual data y are used to compute the residuals (2). The results for trending the residual r_n are shown in Figure 7. The upper plot shows the (low-pass filtered) trend for the Peak EGT residual (the second component of r_n). The lower plot shows the trend for the raw EGT data. As Figure 7 illustrates, trending the model-based residuals provides a significant improvement in the ability of detecting incipient faults compared to the raw data trending. Trending the residual provide a window of early warning compared to the actual observed output.

5 Diagnostics Using Detailed APU Starting Data

More accurate diagnostics of the APU faults can be demonstrated by collecting data from the sensors sampled at a regular interval through the starting duration. The algorithms in this section use such detailed APU starting data and were demonstrated using a high fidelity simulation. The simulation model includes sensor noise, sampling and other features making the data a very realistic representation of the real APU starting data. The simulated data illustrated in Figure 8 was produced with a few faults seeded into the engine model. The diagnostics algorithms worked with the data stored in a file.

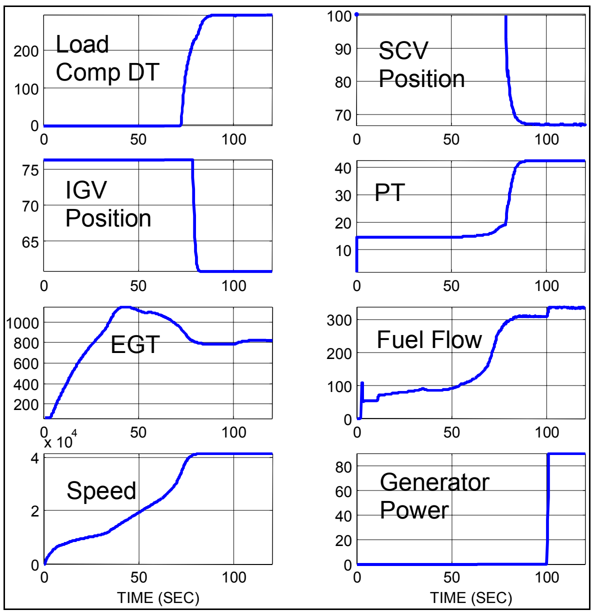

Figure 8. Detailed APU starting data

The prediction model used for diagnostics differed from the comprehensive high-fidelity simulation model. The structure of the prediction model for the APU gas path used for the diagnostics is illustrated in Figure 9. The model consists of two static maps meaning that the output variables can be computed from the instantaneous values of the input variables – no integration of the system dynamics is required. A model built this way is largely independent of the fuel controller (the actual fuel flow is used as an input) and enables an accurate estimation of the faults.

One of the prediction model outputs in Figure 9 is engine acceleration. The acceleration is not measured directly. Instead, in computing the respective residual the predicted acceleration is compared with the numerically differentiated engine speed. Design of the differentiating smoothing Wiener filter for estimating engine acceleration is presented in some detail in [4].

When applied to the APU starting history data, the prediction model can be expressed as a set of input-output equations (an extension of (1))

$$\hat{y} = F(p, u, V), \tag{4}$$

where the vector $\hat{y}$ collects predicted histories of the model output variables through the start data batch. The vector V defines the ambient conditions, similar to (3). In (4), u collects the batch historical data for the variables shown as the inputs to the prediction model in Figure 9. The performance parameter vector p in (4) is used for modeling the engine faults.

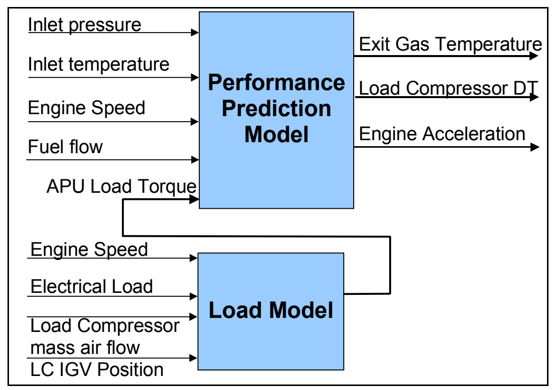

Figure 9. Prediction model for APU performance

In Figure 6, block arrows indicate some of the performance parameters considered. The faults are modeled as performance parameter changes. The mapping between a change in parameter p in (4) and an underlining physical fault was derived by a combination of experiential knowledge and very detailed simulation models. Specifically, the incipient faults modeled include:

(1) Fuel LRU deterioration or fuel nozzle clogging
(2) Parasitic drag torque on the engine shaft
(3) Performance problems in the power section and load compressor of the APU.

The model (4) can be employed for the engine condition monitoring by considering the residual $r = y - \hat{y}$. By linearizing nonlinear prediction model maps for the data batch around the no-fault prediction, this residual can be presented in the form

$$r = r_0 + Sq + \xi, \tag{5}$$

where r_0 is the prediction model offset caused by the modeling errors, the error variable ξ collects all of the sensor noise terms and $q = p - p_0$ is the vector describing change of the performance parameters compared to its initial value. Such performance parameter change would characterize engine deterioration and emergence of an incipient fault condition. The performance parameter change q can be considered as a fault parameter.

The matrix S in (5) is a sensitivity matrix. In the incipient fault condition, the performance parameter change q is small and S can be determined from (4) as

$$S = \frac{\partial F}{\partial p}(p_0, u, V), \tag{6}$$

where p_0 describes the nominal value of the engine performance. The function F in (4) is not available in an analytical form, but can be computed numerically for the given arguments (ambient conditions and the data batch). The sensitivity matrix S can be estimated through finite differences, by a secant method. The finite difference estimation of S requires N+1 runs of the simulation model, where N is the dimension of the performance parameter vector p.

By assuming that ξ is an unknown zero-mean random variable with the covariance $\mathrm{cov}(\xi) = \Xi$. A multiple Linear Regression estimate of the fault parameter q can be obtained from (5) as

$$\hat{q} = \left[S^T \Xi^{-1} S\right]^{-1} S^T \Xi^{-1} r - q_0, \tag{7}$$

where q_0 is the estimation offset corresponding to the prediction residual offset r_0 in (5). The covariance Ξ describes the model of the modeling error and the noise in the data. In practice, this covariance can be estimated empirically from a series of data for a normal operating engine obtained over many flight cycles. Using the fault parameter estimate (7) requires trending to take into account the unknown offset q_0 that is individual for each engine.

The described diagnostics approach is applicable to the APU data in a straightforward way, provided that the data collected at the sufficient rate to allow for the engine acceleration estimation from the speed. The algorithms were demonstrated using the simulated data in Figure 8. The sampling interval was 0.2 s. The fault estimates obtained for this data are compared against the faults actually seeded in the simulation in Table 1. Three faults were seeded simultaneously, each in the range of 2% engine performance deterioration. The obtained estimates are fairly accurate. The worst relative estimation error of about 20% occurs for the power section efficiency loss that is difficult to distinguish in its effect from the fuel system degradation (nozzle clogging).

Fault	*Seeded*	*Estimate*
Power Section Efficiency Loss	0%	-0.49%
Load Compressor Degradation	1%	0.99%
Parasitic Load Torque	0.4	0.42
Fuel System Degradation	2%	2.11%

Table 1. Diagnostics algorithm results

7. Conclusions

The paper has described three increasingly advanced approaches to model based diagnostics of small turbine engines (aircraft auxiliary power units). The increasing complexity of the approaches corresponds to the increasing difficulty of fielding them with the legacy engines. It has been demonstrated that a reliable diagnostics of the faults is possible even from very scarce data collected on such engines. This is achieved through the use of the high fidelity models of the engine available to the engine manufacturer.

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