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Detection and Prediction of the Performance Deterioration of a Turbofan Engine

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ABSTRACT

Many airlines nowadays demand payment for their engine maintenance costs on an hourly-utilization basis. Thus engine manufacturers have become more focused on performance-deterioration modelling and prognostics capability in order to achieve greater confidence in their cash-flow projections. Hence a method for predicting the performance deterioration of civil aero-engines has been devised. The main aims are to achieve significant benefits in mission scheduling and maintenance planning, as well as to reduce both fuel consumption and the costs of maintenance servicing. An example concerning performance-deterioration prognosis is studied.

INTRODUCTION

Jet engines' rotating-components degrade during operation and this affects their performances. (Saravanamuttoo, 1985). So gas-path diagnostics has aimed at detecting, isolating and assessing these changes in performances even in the presence of instrumentation faults. A comprehensive overview of performance-diagnostics techniques can be found in Li (2002b). Related to diagnostics, the goal of prognostics is to predict the engine's or the component's health-condition.

Recently attention has been devoted to developing prognostics algorithms for the analyses of engine performances, within both the civil and military sectors.

Sheuren (1998) described an artificial-intelligence based prognostics and health-management process (PHM) for the Joint Strike Fighter. Thereby the military services aim at eliminating traditional inspections and calendar-based maintenance: remedial actions are preferably based solely on existing condition. Jaw (1999, 2001) and Green et al. (1997) described how the US Air Force included artificial-intelligence based prognostics algorithms in the health management software. A knowledge–based expert-system for prognosis, and its integration with diagnostics results, according to Pratt and Whitney experience, was presented by De Pold (1999). Roemer et al. (1999) approach life prediction by focusing on uncertainty propagation using space-time variant stochastic process models. Hence, a prognostics algorithm for a US navy's ship-propulsion system was discussed by Kacprzynski et al. (2001b). The importance of data fusion was highlighted by Kacprzynski et al. (2001a) and the prognostics value for risk assessment in decision making was described by Roemer et al (2000). A review of the prognostics approach applications to gas-turbine health-monitoring can be found in Byington et al. (2002). Ghiocel (2001) illustrated the application of a hybrid stochastic-neuro-fuzzy-inference process to fault diagnostics and prognostics. Brotherton et al. (2000) proposed an integrated prognosis-process that uses a dynamically-linked ellipsoidal basis function neural-network. They also presented a review of artificial-intelligence based methods. A prototype health-monitoring-and-prognostic process applied for the gas-turbine engine on the US Army M1 Abrams tank was discussed in Greitzer et al. (1999).

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The present investigation focuses on forecasting algorithms, based on time-series models, which are applied to solve prognostics problems in engine-performance analysis: the probability of performance deterioration and its range of magnitude during the next time period of interest are calculated. Two techniques to handle gradual deteriorations in different prognostics problems are presented here. The Box-Jenkins ARIMA method has been used to provide accurate forecasts for immediate and short-term forecasting. Whereas, regression analysis is designed to handle prognoses that require medium and long-term predictions, focusing on physical-based mathematical models of the degradation.

The purpose of quantitative forecasting is to reduce the risk in decision-making. Forecasts are usually incorrect, but the magnitude of the prediction errors experienced depends upon the forecasting method used. The development of forecasting capability is aimed at improving the prediction accuracy and thereby eliminating some of the errors resulting from uncertainty in the decision-making process.

The forecasting methodologies described in this paper will be part of a health-monitoring-and-prognostics (HMP) process that can carry out the following functions: engine-performance analysis and diagnosis; fault identification; prognosis for mission scheduling; as well as maintenance planning.

An advantage of the HMP process is that introducing time-series analysis detects rapid deterioration and treats gradual and rapid deterioration separately, thereby gaining in robustness.

The main goals of the process are to achieve significant benefits with respect to mission scheduling and maintenance planning, as well as to reduce the cost of maintenance servicing. To achieve these targets, the various process functions need to be well integrated and efficiently updated with new information. If an airline's goals of least fuel-consumption and maximum engine-reliability are to be achieved, then it is essential to be able to predict accurately the performance of each of its engines.

DIAGNOSIS AND PROGNOSIS

The research described here has been carried out for a civil three-shaft, high by-pass turbofan. This engine is monitored via 10 measurements (z), the operating condition is defined using 4 quantities (u). The 12 performance parameters (x), efficiencies and flow capacities of the 6 gas-path components, namely 3 compressors and 3 turbines, are calculated through the diagnostics methodologies.

Diagnostics and prognostics algorithms deal with the changes in the values of the measured parameters, calculated as percentage deviations with respect to a baseline condition determined by means of an engine-performance simulation model.

Gradual and rapid deterioration

Fouling, blade erosion and corrosion, worn seals, excessive blade tip clearance and their synergic effects induce gradual changes in the thermodynamic performance of the engine and its components. This results in gradual changes in the set of measurements. Foreign object damage, system failures and sensor faults result in rapid changes in the set of measurements.

Therefore gradual and rapid deteriorations can be distinguished and treated separately. The former implies that all the engine components are deteriorating slowly, whereas the latter may be the result of a single event.

The presence of two different fault-mechanisms and the difficulty in solving simultaneously the two problems with the same algorithm has led to the necessity of implementing two complementary diagnostics methodologies.

There are several algorithms available to address the problem of estimating gradual as well as rapid deteriorations, namely multiple-fault isolation (MFI) and single-fault isolation (SFI) methods respectively (Volponi, 2003).

Traditionally a diagnosis has been mostly performed by inspecting a single-point observation leading to a snap-shot calculation. However for MFI and SFI methods to operate simultaneously requires an algorithm for event detection based on a time-series analysis.

In a similar way as far as gas-path prognostics is concerned, a distinction between gradual and rapid degradations is considered necessary. The forecasting algorithms described in this paper focus on gradual deteriorations. Rapid deteriorations, once detected and estimated, are taken into account in the prognosis through hazard plots specific to the engine and the mission's route.

Prognostics applications

Prognostic outcomes influence directly scheduling missions and planning maintenance. By having an accurate prognosis-capability for a fleet of engines, the maintenance as well as spare-part orders can be planned.

Prognostic capability is critical for:

- Calculating the risk of failure for a given lead time horizon (i.e. risk analysis, performance rejection)
- Optimal management of the fleet (cost balanced against safety)
- Identifying the optimum for the maintenance costs to benefit ratio (costs)
- Combination between the engine-health monitoring process and the engine parts life-tracking process (life usage)

Defining the forecasting problem

Different prognostic problems require different forecasting approaches. Firstly, because forecasting algorithms, which are reliable for a short-term predictions, tend to be inaccurate for long-term horizons and vice versa.

Moreover the nature of the decision to be made will dictate many of the desired characteristics of the forecasting process such as which variables should be investigated, what time elements are involved, what form the forecast should take, what accuracy is desired and what is the availability of the data.

The variables investigated are component performance parameters and measurements. Performance-parameter forecasts are investigated at cruise condition. This study is aimed at predicting the components' degradation levels and their probability in the next future and at estimating the consequent shares of change in specific fuel consumption (SFC) due to each component.

Measurements trends and forecasts are usually studied at take-off (and climb) to guarantee the turbine gas temperature (TGT) and shaft-speed margins.

As far as the time elements are concerned, we distinguish the forecasting period, the horizon, and the interval.

The forecasting period is the basic unit of time for which the analysis is made. For example we might wish a forecast by number of missions (i.e. cycles) or by operating hours. The forecasting horizon or lead time is the number of periods in the future covered by the forecast. Finally the forecasting interval dictates the frequency with which new forecasts are performed. The forecasting interval is often the same as the forecasting period.

The majority of a civil engine's running-time is spent under cruise conditions, which represent operation of the engine at much lower rotational speeds, pressures and temperatures (than during take-off or climb) and hence contribute little to deterioration. Thus deterioration is usually correlated against cycles (forecasting period); where 1 cycle is a flight consisting of a take-off, a cruise period, a descent, and a landing. Another cycle needs to be considered if thrust reversers are used

The forecasting interval is assumed to be the same as the forecasting period. For each mission a new calculation should be undertaken.

Forecasting methods

Time-series analysis uses the history of the variable being forecasted in order to develop a model for predicting future values. To forecast using a time-series, it is necessary to represent the behaviour of a stochastic process by a mathematical model that can be extrapolated into the future, with a given prediction interval.

The accuracy of a forecasting procedure can be quantitatively described by the variance of the forecast error. It is always desirable to have an estimate of the forecast error variance in order to quantify the uncertainty, associated with the forecast. The upper and lower limits of the prediction interval (PI), for a given confidence level, are calculated by adding and subtracting to the forecast a multiple of the standard deviation of the forecast error according to the normal-theory Figure 1.

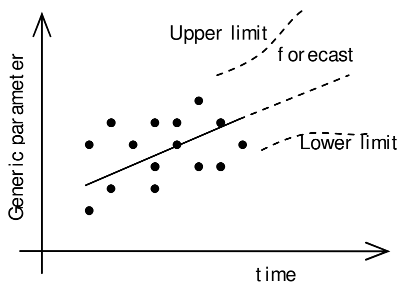

Figure 1: Forecast and prediction intervals for a generic parameter.

Three elements constitute a performance forecasting algorithm, namely a mathematical model of the degradation, a forecasting technique and a procedure to derive the prediction intervals.

PROGNOSTICS MODULE

The HMP process (Figure 2) consists of three articulated sub-processes – Assessment or Diagnostics, Forecast and Operation and Maintenance Manager – these communicate with each other and are divided into modules that perform the actual calculations.

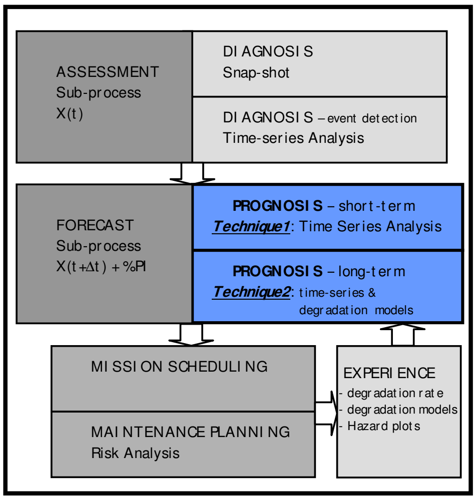

Figure 2: Performance Health-Monitoring and Prognostics (HMP) process.

The diagnostics analysis that precedes the forecasting calculation is performed under two operating conditions. The first is at take-off (and climb) looking at the TGT and shaft-speed margins. The second, under cruise conditions, studies modules performance parameters, such as efficiency and flow capacity. The process includes forecasting algorithms to estimate the probability of a deterioration level happening during the next time-period of interest.

Maintenance support, flight operations, fleet management reliability engineering and quality assurance teams would benefit from the use of the health-monitoring and prognostics (HMP) process that will provide extrapolations and advice based on the expected long-term behaviour of the engine suffering from the diagnosed condition.

Two different prognostics problems

Two techniques are presented for predicting gradual deteriorations in different prognostics problems. Rapid deterioration is taken into account through hazard plots that influence the safety margins.

The Box-Jenkins ARIMA method (*technique 1*) has been implemented to provide accurate forecasts for immediate and short-term forecasting. Its applications in prognostics include:

- failure risk for a short-term lead-time (performance rejection).

Regression analysis (*technique 2*) is designed to handle prognoses that require medium- and long- term predictions: it employs physical-based mathematical models of the degradation. Its applications in prognostics include:

- failure risk for a medium or long term lead time horizon;
- identifying the optimum for the maintenance costs to benefit ratio;
- facilitating the optimal management of the fleet.

An application of the ARIMA technique to the problem of performance rejection is now presented.

Technique 1: ARIMA

The ARIMA method, is a combination of the autoregressive (AR) and moving-average (MA) models (Box and Jenkins, 1976).

The AR model equation can be written as:

$$X_t = \delta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + A_t \quad (1)$$

where X_t is the time series. A_t represents normally-distributed random errors, and $\phi_1, \ldots, \phi_p$ and δ are the parameters of the model, with the mean of the time series equal to

$$\delta - \sum_{i=1}^{p} 1 - \phi_i \quad (2)$$

The autoregressive model involves a linear regression of the current value of the series against one or more prior values of the series. The value of p is called the order of the AR model.

Instead the MA model equation can be written as:

$$X_t = \bar{X} + A_t - \theta_1 A_{t-1} - \theta_2 A_{t-2} - \ldots - \theta_q A_{t-q} \quad (3)$$

where X_t is the time series, $\bar{X}$ is the mean of the series, A_{t-i} are random shocks to the series, and $\theta_1, \ldots, \theta_q$ are the parameters of the model. The value of q is called the order of the MA model.

The MA model is a linear regression of the current value of the series against the random shocks of one or more prior values of the series. The random shocks at each point are assumed to come typically from a normal distribution. In this model, these random shocks are propagated to future values of the time series. Fitting the MA estimates is more complicated than with AR models because the error terms depend on the model fitting. This means that iterative non-linear fitting procedures need to be used in place of a linear least squares fit.

In the standard regression situation, the error terms, or random shocks, are assumed to be independent. That is, the random shocks at the ith observation only affect that ith observation. However, in many time-series, this assumption is not valid because the random shocks are propagated to future values of the time series. MA models accommodate the random shocks in previous values of the time series in estimating the current value of the time series.

However the error terms after the model is fitted should be independent and follow the standard assumptions for a univariate process.

Therefore, according to the autoregressive and moving average models, the ARMA model equation can be written as:

$$X_t = \delta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + A_t - \theta_1 A_{t-1} - \theta_2 A_{t-2} - \ldots - \theta_q A_{t-q} \quad (4)$$

where the parameters have the same meanings as for the AR and MA models.

There are four primary-stages in devising an ARIMA time-series model for forecasting – see Figure 3.

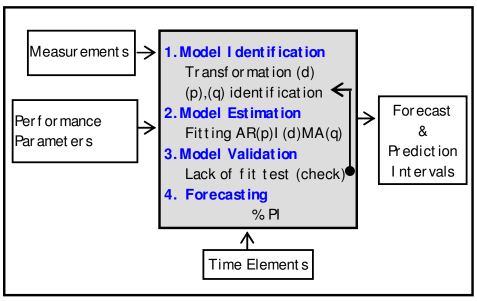

Figure 3: Prediction procedure – *technique 1*.

The advantages of ARMA models are that they are quite flexible due to the inclusion of both autoregressive and moving-average terms.

The application of an ARMA model to non-stationary time-series requires transforming the series. In this case the full methodology is called ARIMA, where the 'I' stands for integrated and the index d indicates the order of the transformation.

The sample correlation functions are used to diagnose the presence of non-stationary behaviours in the data, as well as to indicate the type of transformation required to remove them.

Power transformations coupled with differencing transformations are included in the prognostics algorithm described in this paper: they afford convenient methods of transforming a wide class of non-stationary time-series.

The sample autocorrelation functions and the sample partial autocorrelation functions are then used to identify the indexes p, q that are the orders of the AR and MA models.

According to Box-Jenkins, (1976) the variance of the l steps ahead forecast for any origin t can be estimated and assuming A_{t-i} are normally-distributed, it follows that, given information up to time t, the conditional probability distribution $p(X_{t+l}/X_t, X_{t-1},\ldots)$ of a future value of the time series will be normal with a mean $\hat{X}t(l)$ and standard deviation estimated. Consequently the prediction intervals (PIs) for a specified significance level α can be calculated.

Technique 2: Regression

In regression analysis of time-series, historical data are represented by mathematical models that are analytical functions of time. A general form of model can be expressed as:

$$X = b_0+b_1z_1(t) + ..b_kz_k(t) + \in \qquad (5)$$

where X is the variable we are studying, the $\{b_i\}$ are the unknown parameters, $\{z_i(t)\}$ are mathematical functions of t, and $\in$ is the random component. The random component has an expected value of zero $E(\in) = 0$, and variance $V(\in) = \sigma^2$.

In particular, the three mathematical models of the degradation, described and justified in the next paragraph have the following form:

$$X = b_0+b_1z(t)+ \in \quad t=t_0,t_0+1\ldots\ t_1 \qquad (6)$$

where t_0,t_1 denotes the current time period.

Forecasting consists of estimating the unknown parameters in the appropriate model and using these estimates, projecting the model into the future to obtain a forecast and its prediction interval. Therefore the prediction procedure is divided into two steps: the fitting procedure and the forecasting procedure.

A wide range of techniques can be used to estimate the unknown parameters b_0 and b_1 in the way that the model best fits the observations within the interval t_0,t_1. In this work, the least-square method has been used. The estimates for b_0 and b_1 are chosen to minimise the error or residual.

The procedure proposed here is based on the assumption that the mathematical model is correct. The analysis includes a method to consider the validity of this assumption, which gives as output the best fitted model among the three considered by calculating and comparing the Coefficient of Determination (Montgomery, 1990):

$$R^2 = \frac{SS_R}{SS_{XX}} \qquad (7)$$

where

$$S_{XX} = \sum_{i=1}^{n}(X_i - \overline{X})^2 + \sum_{i=1}^{n}(X_i - \hat{X}_i)^2 = SS_R + SS_E \qquad (8)$$

and

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad (9)$$

R^2 is used to judge the adequacy of a regression model. It measures the amount of variability in the data accounted for by the regression model ($\hat{X}$).

R^2 always has a value between zero and unity, and the closer it is to unity the better the model fits the data. The procedure includes a limited number of models: therefore a threshold value for R^2 has been introduced. If R^2 is less than 0.7 for the all three curves, then none of the three models is suitable. In this case, a different series interval t_0,t_1 should be considered. Particular care should be paid when using different model without a physical justification, for so doing unreasonable forecast could then ensue.

Although regression analysis is part of many forecasting methods, a regression model can be used as forecasting technique in its own right. The regression model can be used for estimation and prediction (Montgomery, 1990).

By estimation, we mean evaluating the mean response over time, that is the wish to estimate $E(X|t)$. The point estimate of this parameter is just the fitted value of the regression model at time t. Then a $100(1-\alpha)$ percent confidence interval for the mean of X at the point t can be calculated, and, as a result, the normal-theory prediction interval for future observations can be estimated.

The prediction procedure, corresponding to *technique 2,* is summarised in Figure 4. Once the time elements are decided, the forecasting method can be used. A pre-processing technique is applied if the parameter under study is a measurement. The data in the time period of interest are fitted with the three models (namely equations (5), (6), and (7)). The best of the models, with the highest coefficient of determination, is selected to perform the prediction. If R^2 is below a predetermined threshold, different time-elements inputs are analysed. The model is extrapolated to the time horizon and the prediction interval is calculated.

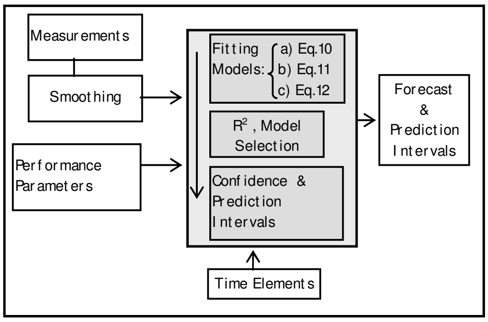

Figure 4: Prediction procedure- *techique 2*.

Technique 2: deterioration model

The failure rate versus time relationship for most mechanical equipment can be modelled with the typical 'bath-tub' curve – see Figure 5. Three phases are distinguished: run-in, design-life and wear-out phases. The failure rate is high at the beginning, then stabilises and increases again at the end of the life (Abernethy, 2000), (Li, 2002a).

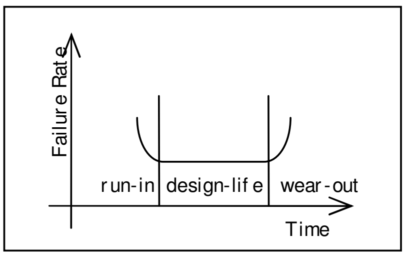

Figure 5: Typical bath-tub curve showing operational phases.

As far as the gas-turbine degradation rate is concerned, we observe that (excluding the wear-out phase) the rate of performance deterioration usually diminishes with use; it starts off at high rate and than settles down to low rate. It is thought that service use imposes distortion loads and differential thermal growths, slightly in excess of those experienced during the post-build engine running-in testing, which further wear seal clearances. There comes a point, in service use, at which no further wear due to the above occurs except under the rare instances of some violent manoeuvre. Thus the mechanical degradation rate diminishes (Crosby, 1986). What of course will still continue, but generally at low rate, will be (i) the corrosion of blades, (ii) the erosion of seals and blades due to contaminant and particles in the air, and (iii) the fouling or deterioration caused by the adherence of particulate contaminants to the gas turbine airfoil and annulus surfaces.

To study and to model the evolution of the deterioration, we can introduce two curves, one for the health-parameter level, Figure 6, and one for the deterioration rate, i.e. its derivative. The curve in Figure 6 shows a generic trajectory of component's health parameter: its derivative, that represents the deterioration rate, follows a typical bath-tub curve. It has to be borne in mind that the curves considered so far represent the statistical behaviour of a given sample of engines (Sasahara, 1986) and not the behaviour of any single engine. The technique described in this paper is based on the assumption that, for the single engine under analysis, the mathematical model of the deterioration does not vary during the short-term that includes the data used for the forecasting and the forecasting horizon. Nevertheless, any error related to this assumption can be accounted for in the calculation of the prediction intervals.

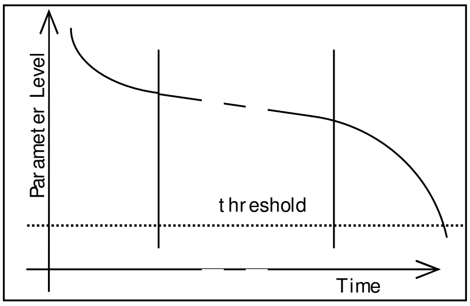

Figure 6: Typical evolution of deterioration, generic parameter. A typical threshold of acceptance for a parameter is shown.

Moreover, in the most general case, if we focus on the design-life phase, three rate trends are possible and therefore are taken into account in the method proposed, as shown in Figure 7:

a) increasing trend (linear)
b) constant trend
c) decreasing trend (linear or non linear)

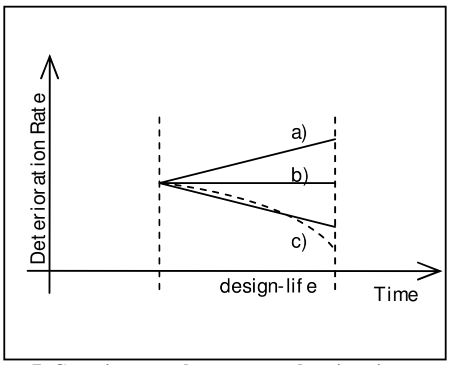

Figure 7: Generic gas-path parameter deterioration rate. Three models during design-life.

The corresponding level curves are:

a) trajectory that curves downwards (negative convexity)
b) straight line trajectory (linear)
c) trajectory that curves upwards (positive convexity)

In the prediction procedure described subsequently, in accordance with other authors (e.g. Sasahara, 1986), the decreasing rate trend (case c) has been chosen to be non-linear.

Typical model trajectories over time of the health parameters are assumed to be the following (Figure 8):

a) $X = b_1\, t^2 + b_0$ **(10)**

for severe deterioration (negative convexity)

b) $X = b_1\, t + b_0$ **(11)**

for linear deterioration

c) $X = b_1\sqrt{t} + b_0$ **(12)**

for soft deterioration (positive convexity)

where X is the health parameter; t is time; and b_0 and b_1 are two coefficients, with $b_1<0$ for decreasing curves.

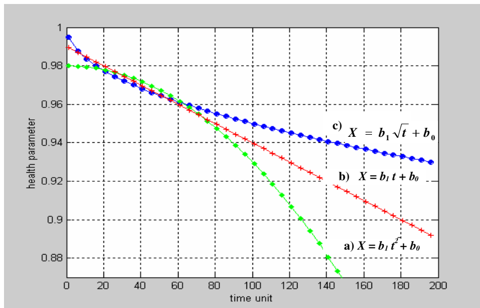

Figure 8: Three models for deterioration level curve. Generic parameter.

Usually gradual deterioration during an engine's life follows a 'soft deterioration model' with positive convexity, and then changes behaviour to follow a 'severe deterioration model' with negative convexity at the end of its life (Figure 9). Life in the context of performance analysis is meant as the period that terminates with the performance being inadequate for the desired purpose, i.e. the engine is rejected from service.

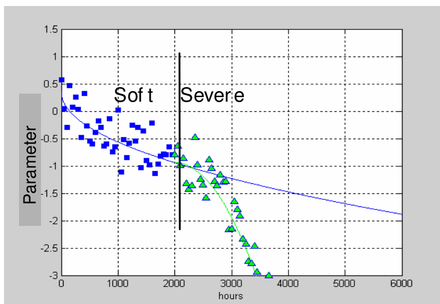

Figure 9: Transition from soft to severe rates of deterioration. Generic parameter.

PROGNOSTICS-MODULE APPLICATION

The potentialities of engine-deterioration predictions are considered via an example.

Performance rejections

These happen when the engine, because of the degradation process, is not able to guarantee the required thrust under the hot-day limit condition.

Civil aero-engines require for certification, a 'maximum take off rating' a 'maximum continuous rating', and a defined 'idle'. Engines ratings are prescribed maximum levels of thrust appropriate to different phases of flight. As far as the take off is concerned, to achieve the same pay-load and range requirements for both sea level and higher altitude runways, the engine has to be run hotter for the airfields at higher altitude, in order to keep approximately the same thrust.

The impact of ambient conditions on an engine's performance can be offset by "flat rating" the T.O. thrust – see Figure 10. This results in an increase of turbine entry temperature (TET) and high pressure shaft speed with ambient temperature, at least up to the hot-day limit of flat rating.

At day temperatures exceeding the limit of flat rating, known as the "Kink Point", the TET is held constant and therefore the guaranteed thrust/p_o reduces.

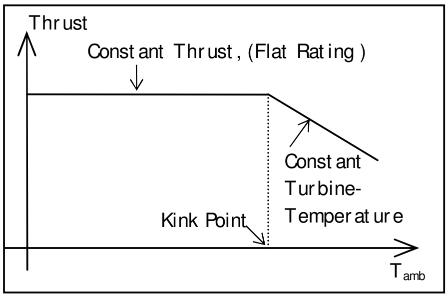

Figure 10: Typical rating curve.

When the engine degrades, the airlines have still to guarantee that it is able to deliver the prescribed thrust under the prescribed conditions (i.e. hot-day thrust). The engine is serviced when this capability cannot be assured anymore, unless the airline reduces the operating-temperature range.

Case Study

The problem addressed in this example regards the probability that the aircraft can complete the next 10 missions, which, in the scenario simulated, is the number of flights before the aircraft returns to the location of the operator's maintenance facility. This investigation is limited to the TGT margin. For a short-time prediction, the HMP process uses the ARIMA algorithm.

Figure 11 shows the TGT percentage changes from engine performance model at actual power level (simulated data) plotted against the number of flights. The ARIMA outcomes are for the 10 flights ahead forecast and the 95% (upper) prediction interval. In the diagram, a safety margin indicating when a corrective action should take place and a warning margin are plotted.

Two conclusions can be drawn by analysing the time-series. The next 8 missions are safe with a 95 % confidence level. A second type of information is that a warning occurrence is predicted to be inside the prediction interval after the flight number 66. This allows a more cost-effective maintenance plan and mission schedule to be devised. This situation may result, for example, in the prognosis that the aircraft can continue to operate between city pairs in cooler climates, in which the engine operates at cooler internal temperatures.

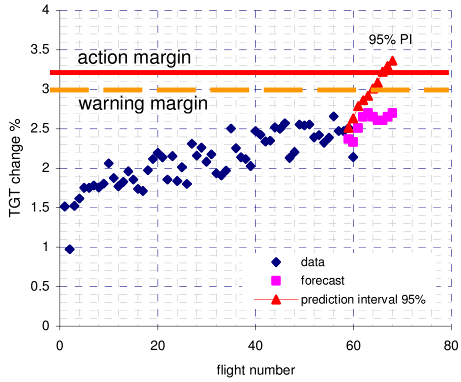

Figure 11: Simulated data – TGT plot. Changes from engine performance model at actual power level. 10 flights forecast ahead and 95%PI.

CONCLUSIONS

'Power by the Hour™' (trade mark held by Rolls-Royce) type of contracts, which includes the capital cost plus a blend of financing and maintenance after the engine's sale, are increasingly being demanded. In a similar manner General Electric's 'Maintenance Cost per Hour™' (MCPH™) contracts and Pratt & Whitney 'Fleet Management Programme™' (FMP™) contracts offer long-term service agreements. These programs provide engines maintenance on a flat rate per engine flight hour basis, enabling airlines to accurately forecast operating costs, reduce cost of ownership and improve asset utilization. The manufacturers have to face this new challenge! In this scenario, performance-deterioration modelling and prognostics capability become issues of prime importance.

This paper focused on the details of forecasting algorithms which can be applied to solve different prognostics problems in engine-performance analysis, calculating the probabilities of a gradual deterioration during various time periods. The algorithms are integrated in a performance-health monitoring and prognostics (HMP) process. Its strength is that by using time-series analysis, rapid deteriorations can be detected and therefore gradual and rapid deteriorations can be treated separately. The main goals of the process are to perform accurate predictions and achieve significant benefit with respect to mission scheduling, maintenance planning and reduction in both fuel consumption and costs of maintenance servicing. Being able to perform such reliable prognostics is the key to effective condition-based maintenance. The potentialities of predicting an engine's deterioration have been analysed, considering both safety and economic factors.

Two techniques to handle different prognostic problems were described. The Box-Jenkins ARIMA method has been implemented to provide accurate forecasts for immediate and short-term forecasting, whereas regression analysis is designed to handle prognoses that require medium- and long-term predictions: it is based on physical models of the deterioration.

A performance-rejection example has been considered. The TGT's percentage changes from the values of the engine performance model under the actual power level (simulated data) were plotted against the number of flights. The ARIMA outcomes were the 10-flights ahead forecasts and the 95% (upper) prediction interval. How the technique assists the prognosis has been discussed.

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