TRENDING OF PERFORMANCE PARAMETERS FOR AIRCRAFT ENGINE CONDITION MONITORING

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ABSTRACT

This paper investigates the trending of performance parameters for aircraft engine condition monitoring. Vibration data is often an indicator of sudden changes in the state of an aircraft engine. Performance parameters, which include pressure and temperature data, usually track slower changes in engine condition. The aim of this paper is to determine precursors to engine events through performance parameter trending. Corrected performance parameters, from regions of steady state operation of an engine, are monitored over a fixed turbine pressure ratio band. The use of corrected parameters from a fixed engine condition provides a basis for the comparison of data from flight to flight. Performance data from a development engine in which an event is known to have occurred is used for analysis. We compare results with similar analyses performed on the same data set in the vibration domain. Tests are carried out using data from three-shaft engines during their development program.

KEYWORDS

Aircraft engine condition monitoring, performance parameters, vibration analysis, trending

1. INTRODUCTION

Engine performance parameters tend to be indicative of medium to long-term changes in engine state. Typically, performance data is used to detect changes such as blade fouling which occur over many flights. Vibration data, by contrast, tends to respond to sudden changes in the characteristic behaviour of an engine.

This work investigates the behaviour of performance parameters in the run-up to an event in a development engine. A comparison is made with vibration monitoring of engines.

1.1. Engine Performance Data

In the performance analysis, the maximum values of selected performance parameters are examined over several runs prior to and including a known event.

In order to compare the parameters acquired at different altitudes, corrections are made to standard day conditions and comparisons are carried out using data acquired over a set turbine pressure ratio band.

Temperature data is referred using theta, the ratio of the intake temperature (T20V) to the standard day temperature which is 288.15 K; pressure data is referred using delta, the ratio of the intake pressure (P20V) to standard day pressure (14.696 psia) [Walsh & Fletcher 1998].

In order to compare engine runs at the same operating condition, the data are examined in the example below for the TPR range 1.0 to 1.4. Each referred parameter is also scaled using the turbine pressure ratio.

2. DEVELOPMENT ENGINE TEST DATA

The data are taken from a development engine in which an IP bolt release occurs during testing. This engine event takes place on Day 208.

2.1. Data Processing

The engine data examined are for 17 test data sets leading up to and including the bolt release event on Day 208. In some cases, there is more than one flight test set for a particular day; for example, there are three sets of data from Day 190. The test sets are analysed in chronological order.

All of the data are first median filtered, using a 5-point window, in order to eliminate outliers. The parameters are examined over a turbine pressure ratio range of 1.0 to 1.4. The aim of analysing data in turbine pressure ratio bands is to compare parameters at similar engine operating conditions. The range investigated is made wide enough here to capture data over several test days. Narrower bands could also be tested given a sufficient spread of data over multiple test days.

Figure 1 shows the distribution of available data for the selected TPR band over the test data sets. The data set numbers correspond to the following test days:

Test data set number	Test day
1	Day 143
2	Day 171
3	Day 175
4	Day 177
5-8	Day 178
9-11	Day 190
12	Day 200
13	Day 203
14-15	Day 206
16	Day 207
17	Day 208

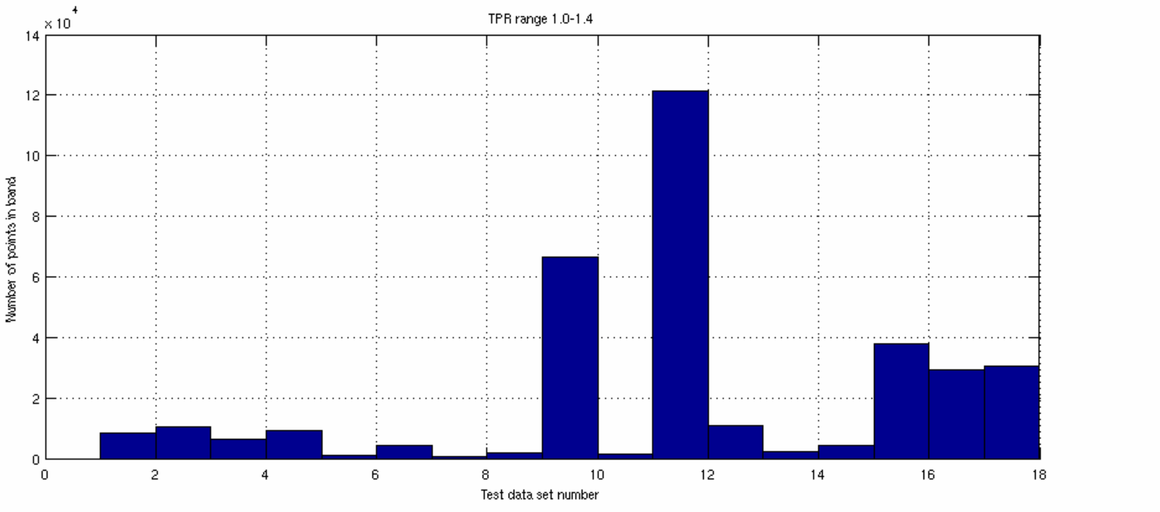

Figure 1 - Data available in the TPR region 1.0 to 1.4 over test days leading up to and including the event day

The data are scaled to account for the effects of altitude. The test engine is controlled against turbine pressure ratio (TPR). The referred data are normalised using TPR, so that data can be compared across differing TPR values (within the band 1.0 to 1.4).

For each referred and scaled parameter, the maximum, mean and median values are plotted over the test sets leading up to the event. The parameters selected for investigation here are the high pressure compressor exit total pressure P30V, the high pressure compressor exit total temperature T30V and the turbine gas temperature TGTV. The high pressure compressor parameters are chosen because they are amongst the dependent variables which might be associated with changes in performance measures such as efficiency and capacity. They can be included in performance analysis exchange rate tables which link changes in independent variables to changes in observables (see, for example, [Provost 1994]).

3. RESULTS

The maximum value of the referred, scaled pressure P30V reaches a peak on flight data set 11, which corresponds to testing on Day 190. As seen in Figure 2, the maximum value jumps by over 8 psia from the maximum encountered in the previous set of acquired data, which is also taken from Day 190.

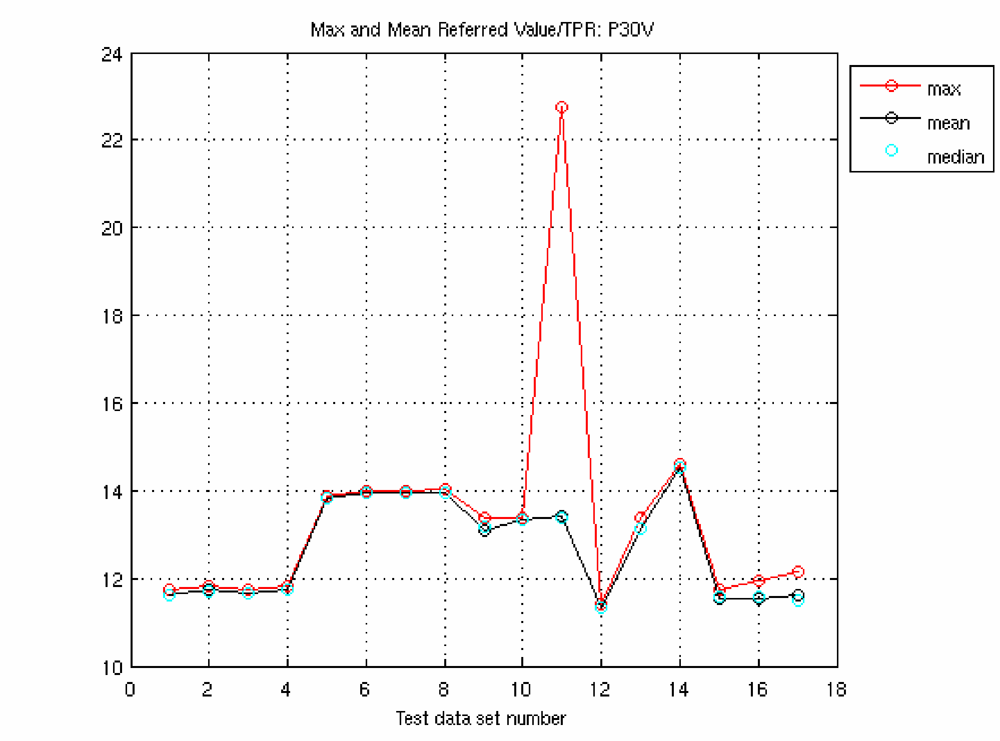

Figure 2 - Maximum, mean and median values for referred, scaled HPC exit pressure

In the case of the referred, scaled temperature T30V (Figure 3), a peak in the maximum value occurs two flight tests after the change seen in the P30V value. This peak is reached on Day 203.

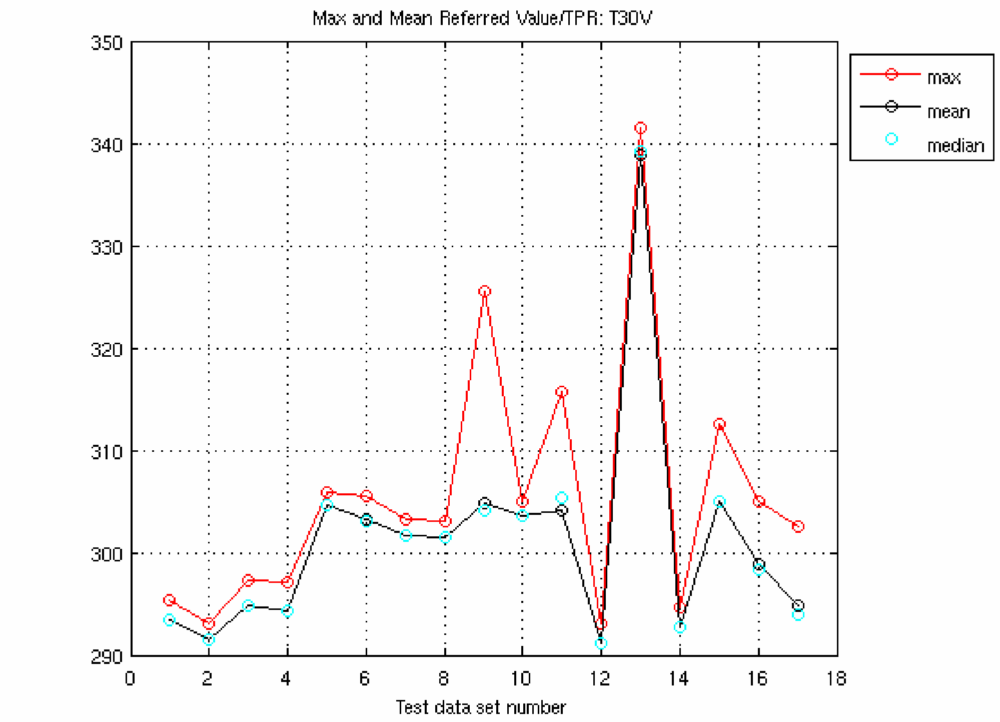

Figure 3 – Maximum, mean and median values for referred, scaled HPC exit temperature

The turbine gas temperature data does not show a sudden jump in the maximum; in fact, the maximum value drops for the test sets 5-8, which all arise from a single flight day, Day 178. The peak in the maximum occurs on Day 206; the maximum value declines slightly after this point but remains at an elevated level on the two subsequent test days (Figure 4).

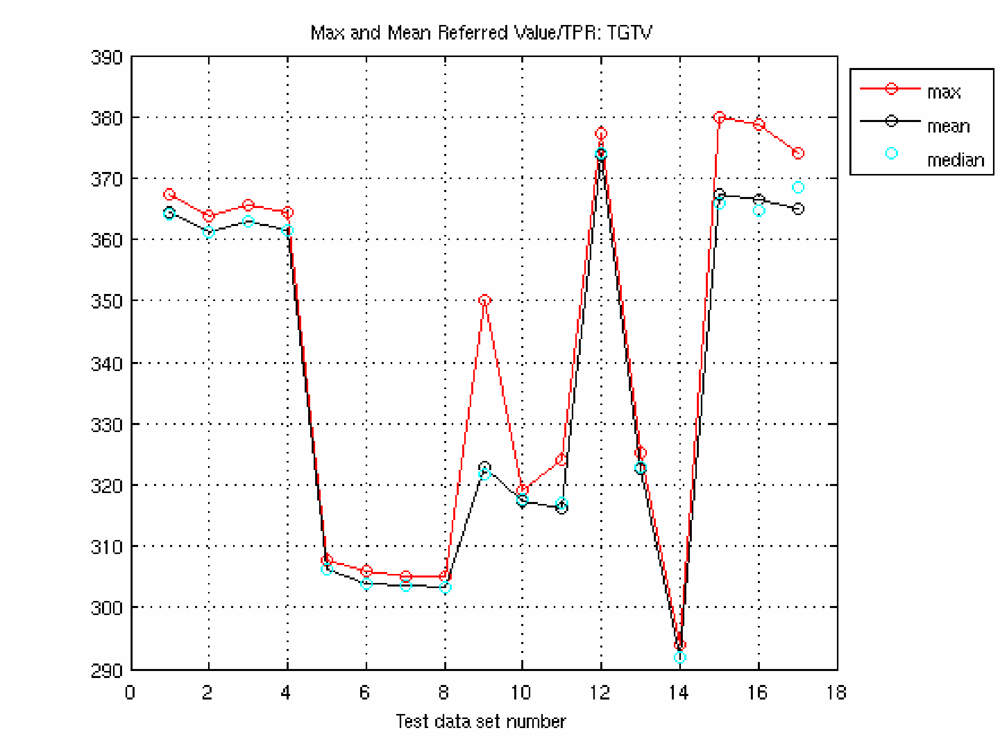

Figure 4 – Turbine gas temperature maximum, mean and median values over the test flight sets

4. ENGINE VIBRATION DATA

Vibration data were collected over a similar period to the performance data, described previously, using case-mounted transducers and the QUICK system for acquisition [Clifton2006]. Tracked orders, a characteristic feature of engine vibration suitable for use in distinguishing normal from abnormal flight data [Clifton2006b], were extracted from broadband spectral data.

Vibration signatures of tracked orders were formed for each flight in the range covered by the performance-based analysis, in which vibration amplitudes are collected with respect to speed (where speed is typically quantised into B = 20 discrete sub-ranges [Clifton2006b]).

One method of visualising the differences between signatures formed from successive flights is described in [Clifton2007]. Here, each signature is summarised by a 1-dimensional quantity; e.g., the total area under each signature curve. Figure 10 shows these extracted 1-dimensional quantities plotted against time for the duration of the test, with a running average superimposed for reference.

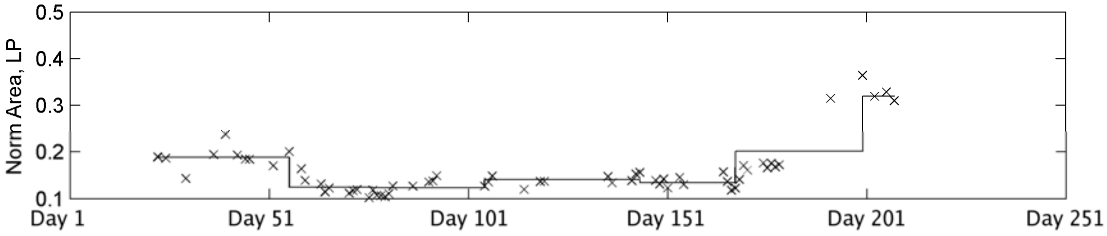

Figure 5 - Plot of tracked order signatures over time, showing normalised area-under-curve

5. DISCUSSION

The aim of trending is to enable the detection of changes in normal engine state prior to an event. In order to be useful, the method must flag genuine changes, but not alert on normal data; it is important that it avoid false positives.

The question which arises is whether the maximum value of the referred parameters could be used to indicate an anomalous engine condition. The change in referred and scaled P30V would seem to be significant, as it is far higher than the previous maxima of the other test days. The peak in the maximum values occurs prior to the event day.

This corresponds with the shift observed in the timeline constructed from vibration data, in which a notable change occurs four flights before that in which the event was observed.

6. CONCLUSIONS

Verification of these observations against a similar analysis performed in the vibration domain confirms that similar discrimination can be achieved using both complementary approaches.

6.1. Further Work

Further testing is required to determine how robust trending of performance parameter maxima is on other flight tests; in particular, for the method to be viable diagnostically there should be a characteristic level for the maxima on normal data for a particular engine.

Over the last three tests days, the trend of the maximum value of P30V is upwards, while that of the median is not. This is contrary to the behaviour seen earlier in the sequence of flight tests. A diverging trend might be a sign that the engine is moving towards an anomalous state; this would need to be tested in further work.

The characteristic maximum level of a parameter might change as an engine is used in service, yet the data still be normal. The issue of adaptive or on-line limit-setting is an area that could be examined in further work [Clifton2007].

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