

Dynamic Alert Generation Technology for Health & Usage Monitoring Systems

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ABSTRACT

Current alert setting methodologies based on setting defect detection alert thresholds for vibration and other Health & Usage Monitoring Systems (HUMS) indicators have many limitations, principally there is necessarily a compromise to be achieved between the true negative and false positive diagnostic metrics. This is true for all alert detection techniques from fixed thresholds through to Support Vector Machines. In this paper we describe techniques, validated using helicopter HUMS data, which do not invoke this compromise and independently minimise both the true negative and false positive rates.

This paper will also demonstrate how the alert processing can be made more robust and overcome the problems introduced by HUMS data being both non-stationary, non-ergodic i.e. characteristics that change both with time and from platform to platform.

Two techniques utilised in the CFAR-Autotrend proprietary alert detection technology are described; a) The Constant False Alarm Rate technique for setting thresholds based on signal amplitude and detecting level changes b) The Box-Car technique for the automatic detection of local trends. These techniques produce alerts that are based on a significant change in local, not global, conditions in the data stream and are not based on an a priori model of the statistics of the signal.

The performance of these techniques on real world HUMS generated vibration data and the engineering of the processes to automatically produce reliable and robust alerts are reviewed. False positives have been verified to be reduced to be less than 10% of true positives; a level where the diagnostics process becomes robust. The sensitivity to defects

is improved to a level where the true negative rate has been reduced to a level where the diagnostic processes can be relied on and the prognostic interval becomes reliable. The consequential impact of this level of performance on HUMS dynamic alert processing is assessed.

The automation of alert processing breaks the link between the number of aircraft fitted with HUMS and the manpower required to process the data. More importantly it will permit the scarce resource of HUMS specialists trained to diagnose defects to be concentrated on that task, not dissipated processing false alerts. For the future the Remaining Useful Life (RUL) realised from the increased sensitivity of the technique is at a magnitude where the benefits promised by Condition Based Maintenance can become a reality.

INTRODUCTION

One of the most important of the Health & Usage Monitoring Systems (HUMS) technologies is the Vibration Health Monitoring (VHM) function, which utilises techniques of varying degrees of sophistication to identify a wide range of defects developing in power train components. Vibration analysis is capable of detecting incipient defects with a high degree of sensitivity so that useful prognostics can be provided. Reliable alerts are required to produce reliable alarms.

In this paper the definition 'alert' and 'alarm' are as in the HHMAG VHM Specification Working Groups Specification(1). There can be many alerts from the HUM processing which when subjected to the diagnostics processing produces a recommendation for maintenance intervention. Thus an alarm, rather than an alert, results in maintenance action being taken. Alerts are therefore part of the diagnostic processing and not the processing outcome.

Reliable alerts are required to produce reliable alarms. A false alarm is an alarm which has resulted in a nugatory maintenance action. There will be many alerts that do not lead to alarms, but these alerts represent an overhead in the processing that needs to be minimised or eliminated. Ideally the processing to produce alerts needs to be automated.

Most HUMS use a simple threshold method to generated alerts. However, in setting a threshold level there is always an irresolvable dilemma between setting a threshold level that is sensitive to the defect, that results in too many false positives, and a level that produces the required false positive rate, but which is insensitive to defects and produces too many true negatives.

This paper reviews a proprietary automatic thresholding and trending technique, Constant False Alert Rate (CFAR) processing and Box-Car trending, that does not require sensitivity to defects to be compromised by the requirement for a low false alert rate and demonstrates that the performance targets for alert detection as defined by ADS 79 (2) can be met to enable Condition Based Maintenance (CBM). This paper restricts itself to alert detection performance and does not address any of the diagnostic or prognostic technologies.

A description of the specialist terms used in this paper to describe the detection of a failure is given in [Appendix 1](#).

PROBLEM TO BE SOLVED

Most HUMS use a fixed threshold method to generated alerts. However, in setting a threshold level there is always an irresolvable dilemma between setting a threshold level that is sensitive to the defect, that results in too many false positives, and a level that produces the required False Alert Rate (FAR), which is insensitive to defects. This is demonstrated in [Figure 1](#) where an optimistic threshold detects the defect, but with a false positive rate of 5 in 1000. A pessimistic threshold set for a false positive rate of 1 in 100,000 does not detect the defect.

Compounding all these issues is the fact that real VHM data is neither statistically stationary nor ergodic. Changes in environment, duty cycle, operator or changing out a component will all change the characteristics of HUMS data over time and amongst components. Consequently over time some or all of the alert thresholds levels will be compromised and no longer valid. Monitoring the performance and the validity of all of the thresholds being applied in the system is critical to maximising the overall performance of the system and thus maintaining its efficacy, but this demands a high system management overhead.

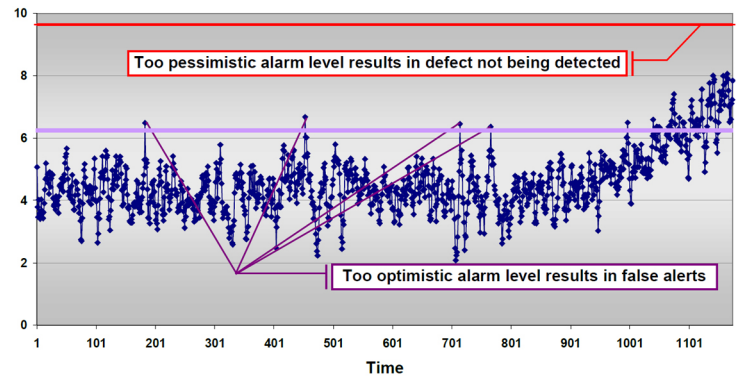


Figure 1. Problems with setting fixed thresholds

Some example data streams from an in-service HUMS demonstrates the non-stationary and non-ergodic nature of HUMS data are shown in [Figure 2](#). These data sets are for the same CI and component, but over different installations across the fleet, thus demonstrating the non-ergodic nature of the data. The data sets contain both long term and short term correlations in the data. The underlying mean of these different data streams both increases and decreases over time and in all cases a threshold set at the start of the data stream would not be valid at the end (non-stationary) and would be different for each installation (non-ergodic).

The key performance measure for threshold setting is the false positive rate. Too few alerts and there is a problem with defect detection resulting in a high true negative rate; too many alerts and there is a problem with nugatory maintenance. If CIs derived from Integrated Vehicle Health Monitoring (IVHM) Systems are going to be relied upon for CBM then both the reliability and robustness of the threshold setting technology has to be very high; that is many more valid alerts than false alerts. Failure to achieve the required reliability and robustness is a major impediment to certification of the VHM diagnostics and hence is a major impediment to the implementation of CBM.

More important than the false positive rate is the false negative rate, which directly impacts aircraft safety and has to be at an extremely low level to support Maintenance Credits; a necessary component for CBM.

APPLICATION OF CFAR THRESHOLD SETTING

The CFAR method of setting alarms operates by splitting the threshold setting process into two stages. Each stage of the processing treats the sensitivity to a defect and the false positive rate separately without compromising the performance of either. A further strength of the CFAR technique is that it makes no assumptions about the statistical or frequency domain characteristics of the data.

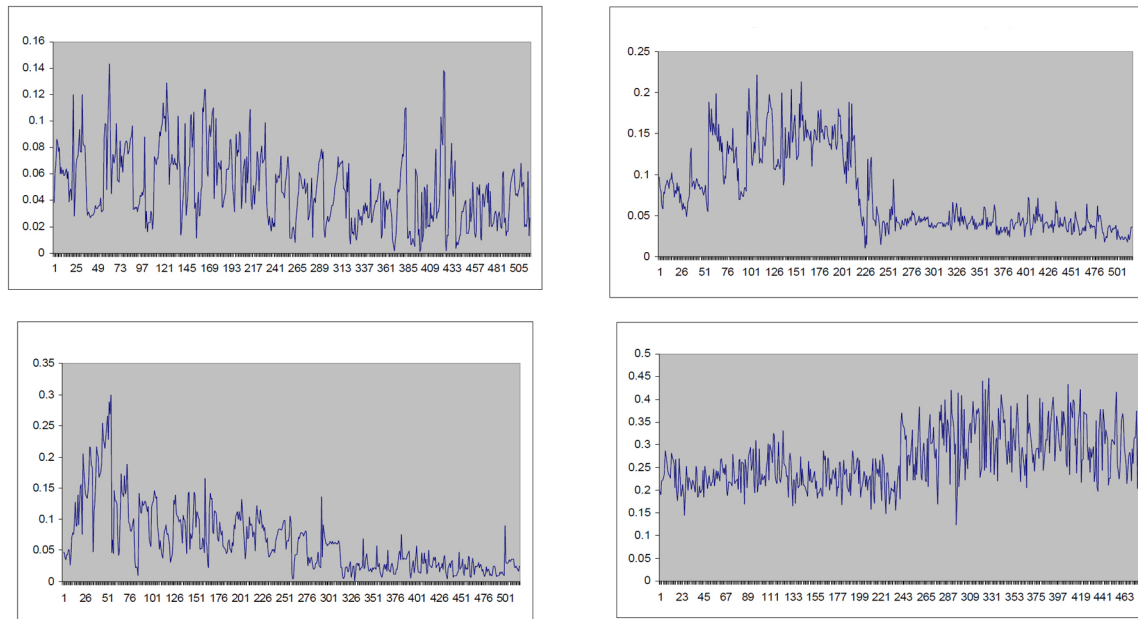


Figure 2. Examples of the non-stationary and non-ergodic natures of condition monitoring data

The processing is described in [Figure 3](#). The first stage of the processing is to establish a primary threshold set at a level that produces a measurable exceedance rate for the data stream. The primary threshold level is controlled by a feedback loop to maintain the exceedance rate at a constant value, hence the descriptor of Constant False Alarm Rate processing. This sets and maintains a threshold maximising the probability of detection.

The secondary stage of the processing deals with the false alert issue and subjects the data that exceeds the primary threshold to a binomial (binary) integration process - also known as M out of N processing (MOON) - to establish that the primary threshold was not crossed due to the random noise component of the data but due to the underlying trend or similar deterministic component of the signal. Trending, or a similar underlying process caused by a defect, as shown in [Figure 1](#), will correlate the data and thus trigger the secondary 'threshold', whereas an uncorrelated noise of the signal without the defect will not.

This secondary processing has the benefit that when an alert is switched on it will stay on, unlike fixed threshold techniques where the noise in the signal causes the alert to switch on and off during the transition.

The amount of Binomial integration is determined by the target false positive rate. As the primary threshold exceedance rate is controlled to be a constant rate, the output of the secondary processing is also a constant. This control allows the sensitivity to defects, the number of valid alerts and the FAR to be managed.

Clearly there are a number of trade-offs to make with respect to setting up the parameters for CFAR processing. The performance is dependent on the characteristics of the HUMS data sets. There are many different data set types in HUMS and it is therefore unlikely that a universal set of parameters can be found. In order to maintain the performance of the CFAR across the data sets, parameters will have to be allocated appropriately to the different characteristics of the data that are employed.

There are a number of thresholds mandated by the design authority or by the HUMS vendor. This technology respects the handbook thresholds by preventing the dynamic thresholds compromising the mandated thresholds. The technology effectively replaces the 'warning' alert levels employed in most HUMS and is strictly advisory in nature. This represents a technology that is easily integrated with current threshold setting philosophies. The processing is entirely automatic and deterministic in nature with no reliance in inference techniques, ensuring that the performance can be easily validated.