# A Framework and Breakdown of Health & Usage Monitoring systems for Aircraft Applications

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## Abstract


A Framework and Breakdown of Generic Health & Usage

Monitoring Systems for Aircraft Application

Melvin Domin Mathew

Asset Management strategies are converting from a reflective/reactive maintenance to preventive and predictive maintenance methods. With the increasing need for higher safety standards and to reduced operational and maintenance costs, the need for methods to diagnose and predict the occurrence of failure is becoming an imminent requirement. With the application of present day technology and non-destructive evaluation and monitoring techniques, this report proposes a framework based on which active diagnosis of the condition of a unit (vehicle/structure) can be monitored towards providing better maintenance practices.

In the world of Rotorcrafts Heath and Usage Monitoring Systems (HUMS) have started to catch traction due to the higher safety standards it provides by continuous awareness of internal working and the reduced maintenance and replacement costs assured by this system. A well developed comprehensive system designed for a specific aircraft platform would be able to analyze critical failure modes, analyze usage and conditional data of the entire structure (extrinsic and intrinsic) and provide a prognostic knowledge to the user/operator and owner of the units.

Within approved safety margins and threshold levels, a HUMS system can provide cost saving by alerting the maintenance crew when the optimal time to change parts are, avoiding underusing or overusing a component, and also to unexpected failures.

This thesis attempts to provide a framework of analysis methodologies and logic flow for a user, engineer, designer or operator to establish a comprehensive HUMS system on a unit so as to ensure the full utilization of present technology. Here Usage-Based Monitoring (UBM) data and Condition-Based Monitoring (CBM) data are collected through sensor networks placed strategically through a Functional Hazard Assessment (FHA) regiment in order to provide the end user and maintenance staff accurate and immediate information on the diagnostics and prognostics of the unit. This allows for better maintenance scheduling, lower labor costs, lower inventory costs and above all safety.

Soon an established HUMS system will be mandatory on most large scale-expensive commercial products such as aircrafts, ships, bridges, etc. so as to ensure the safety of its users and in the long run allow the owners to benefit from the inevitable financial savings that it promises.

# Hypothesis

"Combination of technology and systems placed over a system to monitor its usage and condition will not help in providing improved maintenance capabilities by providing reduced downtime, and reduced use of resources."

## Argument

Over the ages all the way to the modern era the most used form of inspection of structural damages is visual inspection. And this has served us well for the most part alerting us to obvious physical damages and potential danger from failure. In the case of a trained eye an inspector might also be able to notice minute changes in structural integrity in time enough to alert the necessary maintenance staff. But with the complexity of machinery that is used and the innate number of intrinsic failure modes that are potential to it, it becomes tedious and near impossible to maintain regular and periodic checks by professional staff to avoid failure.

The aim of this thesis is to disprove the above statement and prove that appropriate combination of available technological advancements and sensor technology in addition to non-destructive evaluation techniques and robust control systems can help provide improved maintenance capabilities thereby saving resources and optimizing performance down the line. In addition to this I will also attempt to provide a framework on which a user/designer or engineer can establish a working HUMS system to earn the perks of this system.

# 1. Introduction

With the increasing need for effective and efficient asset management, investors owning high value goods have been looking into ways to reduce spend on maintaining their acquired assets. By default then the highest spend assets become aircrafts, space crafts and ships. Since the repair costs of individual components of these vehicles are extremely high, industrial need has triggered a need for academic brilliance to help with this situation. A need for a robust health monitoring systems has then become a part a culture of ownership and in the long run will provide benefits by reduction in resource utilization and outstanding financial benefits.

Versions of the health monitoring have been in use since the 19th century when railroad wheel tappers would strike the rails with a hammer to evaluate if damage was present. The concept that is proposed is not new. Although technological advancement has sky rocketed only since the recent times via initiatives driven by the US Army. This was taken up since repair and maintenance cost endured by these parties needed to be cut down due to asset management programs. Current Health and Usage Monitoring Systems (HUMS) typically perform vibration monitoring, exceedance monitoring while there is research going on with condition based monitoring. Sikorsky recently conducted a study in support with the U.S. Department of Transportation (DOT) and the Federal Aviation Administration (FAA) that addresses usage monitoring and usage based maintenance (UBM). Boeing on the other hand conducted a study in support of the U.S. Army on developing a Condition Based Maintenance (CBM) program that combines the use of both UBM and condition monitoring of components to grant credits to life-limited rotorcraft parts [8].

This technology and concept are however being pursued in the various other fields such as sea and road transport vehicles, civil structures, windmills, etc. Academic and Industrial leaders are realizing the need for effective asset management solutions to increase the longevity of their asset and the need to optimize spend on maintenance. This paper aims to inspire a framework that can be used as the backbone to establish a system based on sensors, Data acquisition networks, fault detection algorithms, usage based maintenance functions, components condition monitoring approaches and finally a proposed survival analysis algorithm that in capable of culminating the data acquire and processed and presenting it to the grounds man providing the maintenance tasks.

The survival analysis algorithm proposed is the use of Cox's Proportional Hazards Model (generally used for medical data processing) along with a Markov model to potentially pin point specific maintenance requirements in order of criticality. The overall aim of a HUMS systems should be to increase the remaining useful life of components and in the bigger picture the entire structure through scientifically backed predictive maintenance strategies. Through long term strategic use of HUMS, financial savings then becomes an inevitable outcome.

# 2. Objective

This thesis sets out to achieve four main objectives. Although they are all inter related, each have their own importance within the field, creating an essential weave in the network of HUMS. The purpose, foundations and introspects will be provided in the subsequent pages. Most of the research conducted for this study was carried out based on rotorcrafts, since most research available is weighted towards this field. However this technology can be extended to other fields of machinery and vehicle usage by a direct extension of this paper.

The four objectives that the thesis aims to address other than disproving the null Hypothesis are:

1. Construct a structural and reason based framework that a typical Health monitoring system would have to employ to ensure that accurate and effective information is processed for diagnostic and prognostic analysis.
    a. Here the framework of rotorcraft HUMS systems will be described in detail with regard to flow of knowledge and the purpose of this sequence. This will cover the system from the sensors end till diagnostic-prognostic information being passed onto the end user.
2. Explain the kind of sensor technologies that are currently available or in development to collect information for analysis.

   a. This section will expand on applications of vibrational sensors, acoustic emission sensor, oil debris analysis and such towards usage based maintenance and condition based monitoring.

3. Identify and explain common methods that have been employed to attain these ends.
   a. Algorithms that are commonly used in each subsection of the framework will be listed here.
4. Propose the use of a Survival Analysis tool that can be used to effectively weigh in UBM and CBM data to display failure critical component based on hazard models and covariate analysis to

These objectives were attained through a process of reviewing research of journals, papers, articles, academic reports and more. The amount of knowledge that is present on this topic is immense and thus this paper is not comprehensive but provide a near accurate knowledge of the field and provides enough fundamental knowledge to motivate a user to pursue the use of HUMS in their active maintenance needs. This thesis may also serve as a foundation of a State-of-the Art paper in the pursuance of a doctorate degree.

# 3. Health and Usage Monitoring Systems

The purpose of establishing a HUMS program is to enable

- Efficient fault detection and Isolation
- Prediction of impending failures or functional degradation
- Decreasing down time of assets.
- Conditional and just-in-time maintenance practices
- Increasing reliability

The primary aim then becomes to improve safety of the vehicle or system under surveillance through active monitoring. As a subsequent requirement then the HUMS program provides enhanced diagnostic and prognostic capabilities, assists maintenance personnel in predicting impending failures and increases the availability of the asset. Down the line, this would then provide reliable service, lower maintenance needs and eventually improved economics.

Since their introduction into the maintenance world, health and usage monitoring systems have caught traction in the oil and gas industry, the military, unmanned aerial vehicles, shipping firms, commercial and business operation. HUMS are designed to autonomously monitor the health and usage of various components in a vehicle and provide diagnostic and eventually prognostic data via comparison with pre-set threshold levels and fleet data. This then becomes an application of Non-Destructive Evaluation techniques put to its highest potential. For a rotor craft an embedded HUMS system is capable of tracking, rotor stability/balance, bearing vibrations, structural and transmission usage and condition, oil debris analysis, thermal analysis and much more. Subtle changes in each individual components can be monitored against a threshold level to forecast failure probabilities. Subsequently extreme usage conditions can be recorded to check for structural integrity in comparison to a damage faction calculation and fatigues analysis.

Consolidated information gathered from these techniques can be used to prioritize maintenance needs for the ground personnel and alert them to where their attention is required. Eventually reducing labor time on redundant checks for systems that are in optimal functional condition. This also provides a method to store usage and condition data at each point of the vehicles life cycle providing deeper insight in to future design parameters and optimal usage conditions. Thus the benefits of an established HUMS system cannot be overlooked.

# ***Benefits of HUMS***

A HUMS program can greatly enhance safety management, reliability, asset availability, maintenance and savings on operational and support cost. With the information that can be deduced from the network of sensors and processing algorithms across each stage of the health monitoring system, maintainers can easily identify near failure components and change them at the optimal time instead of prematurely changing them when they still have a safe margin of remaining useful life.

The US Army in fact has a large interest in HUMS and large CBM programs, investing in research and since equipping over 2,500 aircrafts with onboard systems and ground support equipment. This program has been installed in over 4 different rotorcraft platforms including the Apache 64D Longbow Attack Helicopter and the UH-60A/L Black Hawk. As early as 2000, the benefits of HUMS were becoming apparent. For that year, the US Joint Helicopter Safety Analysis Team (JHSAT) found that part/system failures caused approximately  26% of the helicopter accidents in 2000. The JHSAT also reported that 24 (47%) of the part/ system failure accidents might have been mitigated by the use of HUMS or equivalent systems [5]. However with evaluated usage of active HUMS systems analysts found discovered 12-22% decrease in parts cost per flight hour for HUMS-equipped helicopters from 2007-2009 [1].

## *Safety Benefits*

Since implementation there are numerous examples in aviation today where a fault was detected early enough to avoid an emergency landing, or possibly even a catastrophic failure during flight. Safety benefits of HUMS include, but are not limited to:

- Accurate identification of faults prior to catastrophic failure
- Informed decision-making
- Risk mitigation and avoidance
- Lower risk of failure in flight
- Lower risk of emergency landings

*Maintenance Benefits*

HUMS enable failures to be identified in advance, so that plans can be made to avert hardware failure and system damage. The ability to monitor the condition of system components allows for a more efficient maintenance regimen. Maintenance benefits of HUMS include, but are not limited to:

- More efficient maintenance, as unscheduled events can be pushed to align with scheduled actions so the vehicle/system is being used or making money instead of waiting for a parts shipment
- Elimination of the need for portable equipment installation and reduction of the need for additional maintenance
- Troubleshooting and diagnosis of potential faults through proper use of the system
- Deferment or elimination of certain maintenance inspection intervals as HUMS mature
- Diagnosis of problems before they cause collateral damage

*Readiness Benefits*

For commercial fleet operators and military units like, aircrafts, ships and such, readiness is extremely important. Time is money. Readiness benefits of HUMS include, but are not limited to:

- Demonstrable reduction in downtime for unscheduled maintenance events
- Proactive maintenance, allowing unit downtime to be a scheduled and anticipated event rather than an unexpected inconvenience
- Immediate recognition of a seemingly insignificant problem, before it turns into a significant one, allowing for better planning of operation.

*Operations and Support Cost Benefits*

Identifying faulty components and performing maintenance prior to failure occurrence would reduce repair costs and avoid collateral damage to be inflicted section. Further, the ability to replace or repair a part before it breaks will result in increased operational time and consequently increased revenue. For example, the US Army's H-60 platform has several gearboxes that share an oil system. Before HUMS, when a chiping event occurred in one of the gearboxes, all connected gearboxes were removed. With HUMS, the offending gearbox can be quickly identified and removed, saving significant resources. Operations and support cost benefits include, but are not limited to:

- Increased useful life and efficiency by recommending changes to system components such as shaft alignment or gearbox design. Frequently, one damaged part will go unnoticed, eventually resulting in a severe malfunction and the need to replace an entire gearbox
- Identification of certain problems that warrant grounding the unit immediately, thereby preventing further damage, and resulting in a cost savings through averting damage to components other than the root cause
- Extension of the life of a units structure and integrity by reducing overall vibration and collateral damage.

*Other Intrinsic Benefits*

The following are additional benefits reported through a HUMS program:

- Increased user confidence
- Ability to more effectively plan maintenance actions over the long-term
- Ability to monitor health of an entire fleet, regardless of physical location
- As the program matures, the potential to predict when certain faults will occur, based on historical data and specific unit data

# 4. Framework of a generic HUMS system

The conception of HUMS begins at the time of product procurement. Once the unit/system has been procured, it then transfers responsibility down to the asset management. These are the people that are responsible for functioning life of the product and its upkeep. It is to optimize this process that the idea of Intelligent Maintenance Systems get conceived. The framework of technological application requires meticulous criteria within the realms of logic flow, technological capabilities and reasoning. Over-stepping or under-stepping any of these boundaries can lead to inefficient or unusable results.

<table>
<tr><td>Data Acquisition</td><td rowspan="3">Condition Monitoring</td><td rowspan="6">CBM</td></tr>
<tr><td>Data Manipulation</td></tr>
<tr><td>State Detection</td></tr>
<tr><td>Health Assessment</td><td>Diagnostics</td></tr>
<tr><td>Prognostics Assessment</td><td rowspan="2">Prognostics and Health Management</td></tr>
<tr><td>Advisory Generation</td></tr>
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Table 1: Functional Layers of CBM [2].

# ***4.a Identification of Critical components.***

The first task would be to identify critical components that need to be monitored. For this a standard functional hazard assessment (FHA) and a failure modes, effects and criticality analysis (FMECA) processes are usually carried out across the system. Generally the FHA is a top-down approach to identifying significant hazards to unit/vehicle functionality and hence safety. For example, the loss of the main transmission system or over heating of the engine could cause a catastrophic failure. The FMECA however is a bottom-up analysis of credible failure modes that are relevant to significant FHA-identified hazards, including analysis of cascading effects, end-item impact, and resultant criticality of the failure mode before and after taking into account mitigating actions. Credible failure modes have a reasonable probability of occurring, which may cause a system or component to go beyond a limit state, causing a loss of function and/or secondary damage. FHA and FMECA processes use engineering and user judgment, probabilistic risk analysis, engineering tests, and/or actual occurrences of field failures to establish credible hazards and failure modes that are likely to occur. The structured FMECA process naturally results in identification of the process' weakest links allowing directed attention toward the process points of failure and the development of appropriate mitigation strategies [9].

The FMECA then:

- Determines the effects of each failure mode on system performance.
- Provides data for developing a fault tree analysis and reliability block diagram
- Provides a basis for identifying root failure causes and developing corrective actions

- Facilitates investigation of design alternatives to consider high reliability designs for future production

As a result of this analysis the system will then be able to highlight potential single point failures that will require corrective action and subsequently rank each failure mode depending on criticality of the same in terms of unit/vehicle mission and personnel and equipment safety [10]. It will then be these potential systems or subsystems that will need to be monitored for potential failures/damage factions. Monitoring of these systems require then individual research functions where we need to identify what and how are the optimal methods to identify the state of the failing component and its subsequent diagnostic analysis. The first step is then strategic sensor placement.

## ***4.b Sensors Theory and Application***

*Installation Validation*

The FHA or FMECA identifies and assesses credible faults at all points in the process, which are then considered in the design to reduce the likelihood of occurrence. Further mitigation strategies are incorporated to reduce rate of faults and control their impact on critical functions. However for faults that are functionally implausible to alter a sensoring network will be placed around so as to pick up the subtle and drastic nuances that the system/unit will undergo during (extended) periods of usage. Due to economic reasons the points of placement and the kind of sensors chosen are critically analyzed for their capabilities and support function, the aim being to enable the network to provide a level of redundance to other faults being diagnosed.

Therefore in establishing a HUMS sensor network the key concerns of the engineer would be reliability of the sensor, compatibility and sensitivity, cost and placement strategies.

*Data Quality and Sensor Reliability*

Sensing faults generally include, noise, drift, saturation, out of calibration and vibration induced errors. However sensor circuits might provide degraded data depending on uncontrolled local variables such as temperature. Thus this degraded input will provide incorrect result on the diagnostic algorithms that provide processed/derived output values. Thus on a subset level of sensors, a self-sustaining health monitoring system must be secured to assure the reliability of the data that is streaming out of sensors placed across the structure under surveillance.

*Sensor Health Monitoring*

Given that the HUMS employs input data that is generated from sensors placed across the system under inspection, sensor health becomes a primary concern to maintain the robustness of HUMS output data. Thus, a validated and verified sensor health monitoring system that can be applied to a variety of data types will be a resourceful tool. This system should be capable of conducting condition based maintenance support on the sensors themselves [8].

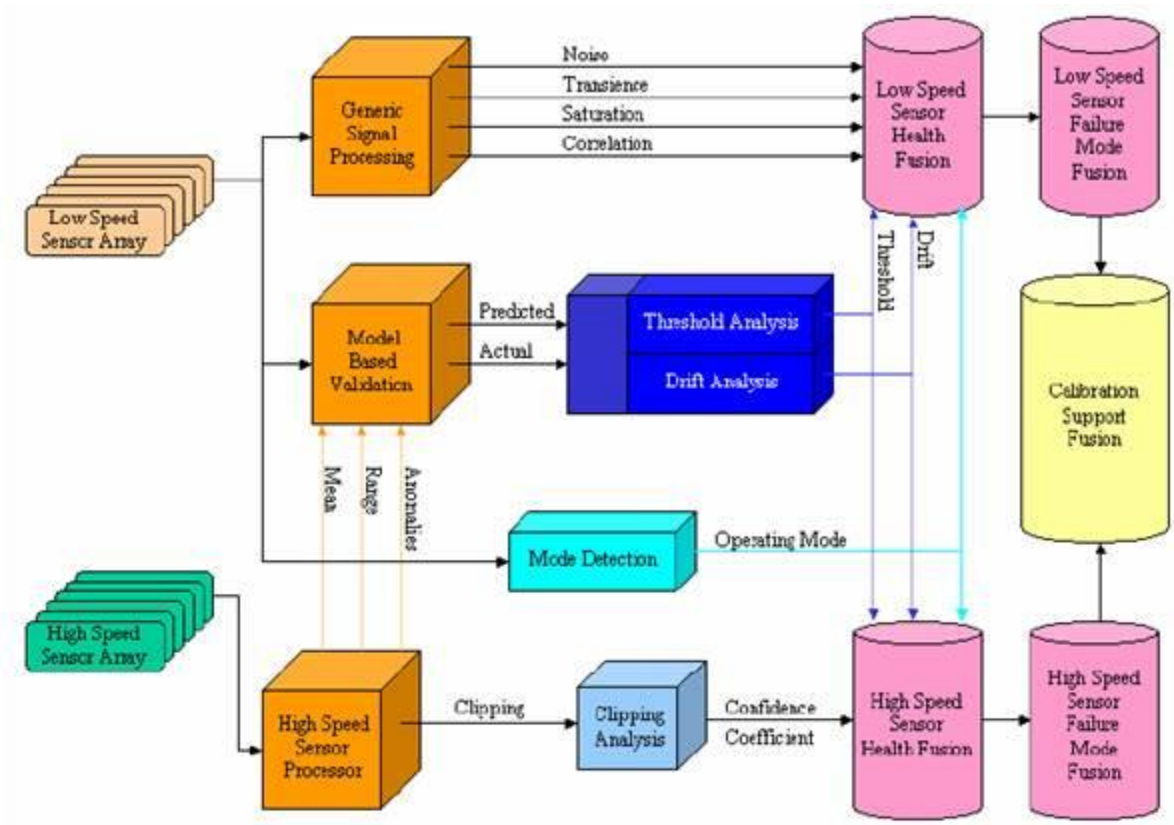


Figure 1 : Internal Architecture of Sensor Validation System

Here a mode detection algorithm is used to recognize whether the sensor is transmitting transient or steady state data enabling us to mitigate false alarms. In addition to this a failure mode assessment is added since the calibration/ maintenance level the sensor requires would be based not only on the health of the sensor but also the type of failure. The following are techniques used to deal with the low speed sensor array and high speed sensor array [8]:

Low Bandwidth Techniques

Auto-Correlation:

This algorithm compares the present data set with recent data sets checking their degree of correlation. Sudden spiking or signal dropout in the data will cause a drop in the degree of correlation and an increase in the probability of random correlation.

Sensor Saturation:

This is basically an out of range check that is performed with incoming data. Often if a sensor fails the value returned by it will be significantly out of bounds than its expected range.

Model Based Validation:

This algorithm checks current data values against historical "healthy" data and then uses the normalized Euclidean distances to predict what the current data should be if the sensors were healthy. Thus, the MBV algorithm generates a 'predicted healthy value" for each sensor input based on an empirical model of how that sensor reading relates to all the other sensor reading. MBV calculations are carried out for both Low Speed Data and High Speed Data.

Threshold Analysis:

Here an upper limit is set on relative difference between predicted and actual values where the relative difference is calculated as the actual difference divided by the overall expected range of the measured value.

High Bandwidth Technique

The high-speed processor, for each step time, calculates clipping, mean, range and anomalies and subsequently generates thresholds for each.

Clipping:

Points which are out of the sensor's range are clipped via hardware or software and return a confidence coefficient based on the amount of signal loss.

These outputs are sent out along side confidence coefficients that can be used for fusion calculations. Presently, there are three data fusion processes that are employed to determine the health of the sensor and subsequent maintenance actions if required. The first one the sensor health fusion determines if the health of the system is in question. The second fusion, failure identification process, analyzes response signatures generated by output features to determine the most likely mode of sensor failure. The third fusion module consists of properly alerting the user and tracking the history of which sensors have identified failures [8].

Therefore sensor hardware reliability and software becomes an essentiality to promise data integrity. Data must be extracted via the digital bus thus reducing effect on data integrity. Periodic validation of parametric data by the operator will assist in evaluation of functional assurance and assessment of "undetermined" nonsensical data [9].

# *4.c HUMS Data acquisition and processing*

The DAC is where all the data collected from the sensors that are placed around gets collected. Anatomically then this is the tip of the brain collecting information from the neural networks spread across the body. Information from here is then processed through a signal processing unit, based on predefined algorithms to establish the condition of the monitored body. In a fixed (monitored) structure, the DAC and the Signal Processing Unit (SPU) can be established together making data transfer much easier and accommodates immediate results for the maintenance staff. However in the case that a vehicle is being monitored, the DAC and the processing units cannot be established in the same body for reasons such as weight, resources, power requirements, space etc. In this case there then has to be a trade off on the kind of monitoring data that the user essentially needs for safe operation of the vehicle versus the resources for it that will affect the vehicles optimal capability. For example, a rotorcraft cannot carry all the processing equipment on the craft, since payload weight affects the capability of flight.

A solution here then is the nominate only essential analysis on board the vehicle and enable a data storage unit, from which the data can be transferred to a ground station for in depth processing. Ground station (GS) post processing also provides the option of comparing individual unit data across fleet data. A single GS unit can process diagnostic and prognostic data for numerous units, providing much needed threshold values and effective analysis.

*Onboard HUMS data Acquisition and Processing*

During the operation of a unit, the HUMS onboard system (OBS) continuously monitors and processes discrete data acquired at required sampling rates to calculate regimes and usage via regime recognition (RR) algorithms. Subsequently both raw and processed data are stored in the data transfer unit (DTU). Thus the primary intrinsic failure modes that can be expected are hardware and software failures affecting data processing and storage. With the data acquisition system then the primary concerns that the engineer should look into would be data storage, data anti-corruption methodologies (between system to system transfer and during storage) and if needed encryption strategies.

Enforcing a system for HUMS data acquisition and processing can increase reliability on the parametric and post processed data. In addition to this internal automated QA algorithms can be designed to compare individual RR and usage data with respect to fleet data. Any abnormalities can be flagged for further investigation. In the case of corrupted or missing data, composite worst case (CWC) usage data can be implemented to maintain safety levels [9].

*Data Transfer between Aircraft and Ground System*

Data transfer from the DTU to the Ground System (GS) can be done via a combination of automated, semi-automated, or manual processes. The primary risk here is the corruption or loss of data during the process along with maximum data storage capacity on the data transfer unit (DTU). Data corruption can be corrected via process automation or checksum error detection and correction. However this provides data integrity only against accidental corruption as opposed to malicious attacks. Clearance to the DTU and the GS can be checked by the operator as a mitigation strategy towards these attacks. Data loss/corruption can be addressed by adding the pilot debrief feature (which includes acknowledging or correcting HUMS reported flight hours and data anomalies) as part of the operator post flight procedures. Automated algorithms can also be developed to detect flight hours independently and compare them against the length of the data received [9].

### *Fleet Data Collection and Storage*

Data received from the HUMS and ongoing maintenance records must be collected and stored for use of calculating usage and CWC of the fleet. Generally it is preferred that the original equipment manufacturer (OEM) maintains this data for comprehensive fleet information. This comprehensive consolidation of data will enable the OEM to improve design concepts and maintenance strategies for the product. However the possible concern within this process is the loss of data or corruption during storage.

To address this concern a copy of the data is made and placed in an archive folder once it is received from the operators, via an engineer in the loop approach, thus maintaining data integrity. This archived folder can then be periodically shifted to an external hard drive / storage space (ensuring back up in case of server crashes or unexpected defaults) while, again, ensuring data integrity [9].

### *Data Mining and Part Condition Monitoring*

Data Mining can be carried out to analyze and scrutinize the service history and a adjust CWC of specific parts. This includes mining a large amount of data for the fleet or at least a subset that ensures statistical significance to the fleet. Because of the large amount of data being mined automated data mining tools will have to be employed to extract data from the archive which could suffer data loss, data corruption, extraction errors, incorrect data, etc.

Automated data integrity checks need to be performed as the data is being extracted. Independent strategies can be developed to allow crosschecking of results during periodic process audits. An engineer can ensure that information regarding integrity of data and part condition is accurate and confine to standards [9].

*Usage and Fatigue Damage Trending*

Once the relevant data is mined, it can be used to calculate usage trends and fatigue damage rate that are used in calculating remaining useful life (RUL). Periodic monitoring can ensure that operators do not go beyond CWC assumptions.

Clustering algorithms can be employed to use the onboard RR algorithm output to develop CWC usage database to establish RUL's for life limited parts (LLP's). This off board approach defeats the need to develop sophisticated onboard algorithm to achieve UBM credit. The clustering algorithm can also be modified to calculate reliability factors (which are significant in UBM credits) providing quantitative data that monitored usage data is compatible with baseline system integrity level. Clustering outputs and usage calculations must be checked for quality and validated [9].

From the results of the above clustering algorithm accumulated fatigue damage can be calculated and compared against the expected damage trend for the CWC spectrum. Thus the error rising in the mapping of CWC usage spectrum will affect the calculate fatigue damage the most.

## ***4.d HUMS Diagnostics***

Now that we have laid out a framework for placing sensors around the structure/unit, evaluating health of the same to enable higher confidence levels and mentioned methods to collect data from the system while maintaining data integrity. The next step is to analyze the kind of data coming from the sensors and use this as a method to deliberate the condition of the component.

From the data collected, different methodologies can be used to cluster diagnostic data, towards providing an updated CWC based on usage. However the complexity of the algorithms and the structure then has a trade off. A simple components or unit under surveillance can be judged via a physical model, where the processor is taught the failure physics and what to look out for. However the units that would generally be under surveillance would be extremely complex structures for which a physical model analysis would be near impossible.

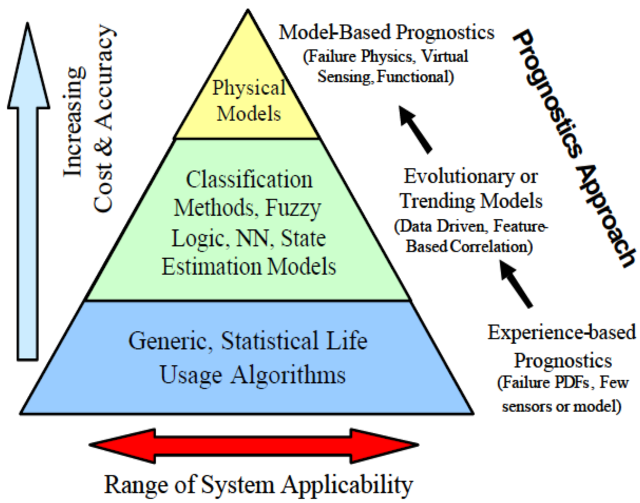


Fig 2 : Prognostics Models and its Applicability

The present state of prognostics is with data driven and feature based correlation models. It enables fuzzy logic, neural networks and artificial intelligence software to make decisions along the process chain to decide whether the part is still working within optimal conditions. In a data driven system, multi sensor data fusion is the preferred method to track a failure mode. A single data type will rarely provide evidence of a particular malfunction that is as conclusive as when multiple data types can be compared. This provides a higher confidence level and makes CBM more convincing. Thus we can say that Data Fusion across multiple sensors offers potentially significant improvements in robustness and accuracy in fault detection and isolation. This also ensures the reduction of false alarms [2].

Before Diagnosis or Prognosis regarding the health of a system is considered, there is the need to identify and isolate the fault and accurately pin point the type of fault. The general process of this is known as Fault Detection and Identification (FDI). A FDI system would take in current monitored parameters as inputs and produce one or more fault indicator signals called residuals. The residuals are analyzed and based on a binary true/false to fault presence, isolation processing starts [6].

There is a variety of sensors (piezoelectric, eddy current, thermal imaging, optical) that have been designed for non-destructive in-situ temperature, vibration, acoustic emission (AE), oil analysis, electrical signature analysis (ESA), ultrasound and other measurements. Among these vibration monitoring and analysis is the most recognized, informative and applicable technique in rotating machinery condition monitoring and is used in combination with all the mentioned measurements [2].

### ***4.d.(i) Analysis Provisions***

Based on the kind of system being evaluated, there are two forms of monitoring that can be undergone. For static structural monitoring like bridges, buildings, etc. plain condition monitoring would suffice based on parametric conditional data such as vibrational analysis, accelerometer data, and such. But in the case of units that are in dynamic motion and where most fatigue levels are caused due to continuous change in movement, such as flights, ships and cars, the usage would play a significant role in determining the condition of the structure on a macro scale.

Most components of such systems are built within a CWC spectrum that is provided by the OEM and subsequent replacement/refurbishment periods are detailed to the maintenance staff. However in most if not all practical cases these components are not pushed to their designed extremes, rather within a safety margin of the same. Thereby we can safely conclude that if a thorough monitoring process is established within the structure to monitor dynamic motion we could add more usage time to the component. On the flip side if the component has undergone higher stress levels and usage than designed for an established monitoring system will be able to pick up on that and alert the user and the maintenance team about the imminent danger thereby providing the essential safety net and reducing collateral losses.

### **4.d.(ii) Usage Based Monitoring**

Regime Recognition Algorithms

The damage factors for each component of a system are assigned by the OEM based on stresses in the unit when undergoing a given maneuver. Therefore, it is important that the regimes can be recognized correctly during the usage of the unit to avoid either underestimated or overestimated damages. This is then an important aspect related to the certification of a HUMS system [12].

So far most of the research conducted in the field of RRA is for rotorcrafts, since they experience the higher stress cycles on maneuver conversions. Therefore this section will cover the topic on the case of rotorcrafts, however it should be noted that this technology can be easily transferred to any other dynamic units for which usage is a high impact component in health monitoring.

One research paper worth mentioning here is the paper by Teal et al., 1997 which describes a method to map flight maneuvers state into the MH-47E basic fatigue profile flight regimes in a manner that ensures conservative, yet realistic, assessment of critical components RUL's. With a reported accuracy rate of 90%, this logical test method identifies maneuvers based on flight experience and mathematical models correlated with flight test results to map the maneuver state into one of the many basic flight fatigue profile regimes. Although here noise was a major concern [11]. Albeit there is much work into automatic regime recognition algorithms using neural networks to map the same. Eventually we come to realize that regime recognition is basically a data mining problem where the system has to sort to measured parameter data and map them into the given regime ID's.

Damage Fraction Calculation.

Boeing in 2010 released a paper written on calculating damage fractions based on regimes identified. The RRA output for each flight generates the sequence of regimes flown along with the time spent in those regimes. In addition, all event based maneuver occurrences for the flight are also identified. Fatigue damage is tracked for high cycle fatigue loading (i.e. multiples of rotor rotational frequency loads within a regime) and low cycle fatigue loading (maneuver to maneuver peak load variation including ground-air- ground cycles (GAG) cycles). The component high cycle fatigue damage for the flight can then be calculated , as illustrated in the equation below, in two parts: i) Sum of damage rates for the regime multiplied by the time in regimes and ii) Sum of damage for number of maneuver event (such as control reversals) occurrences [13].

$$DFChigh = \sum_{i=1}^{n} Dr_i \times T_i + \sum_{j=1}^{m} Dc_j \times C_j \quad \text{Eqn. (1)}$$

Where $DFChigh$ = Component damage for the flight based on RRA

$Dr_i$ = Damage rate for 'i' regime (damage/hour)

$Ti$ = Time in maneuver

$n$ = Total number of time based maneuvers

$Dc_j$ = Damage per event for 'j' occurrence

$Cj$= Number of 'j' event occurrences

$m$ = Total number of event occurrences

The component low cycle fatigue damage for the flight is calculated by first establishing a sequence of loads based on the RRA output sequence of regimes and the corresponding regime maximum and minimum loads. Cycle counting using rainflow-counting algorithms (Ref. 22) is then applied to this load sequence to generate fatigue load cycles. These loads are then used to calculate low cycle fatigue damage. The total damage is then the sum of the high cycle damage and the low cycle damage [13].

The clustering algorithm maps the RR output directly to a CWC regime events. This algorithm is driven by a semi-automated process that ensures engineering experts are in the loop.

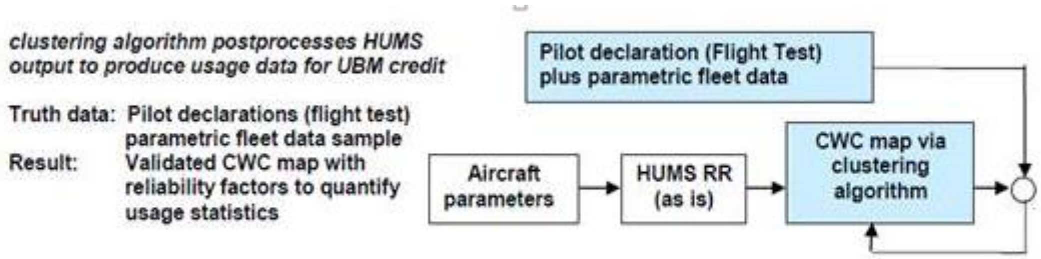


Fig 3 : Clustering Algorithm Concept

This algorithm basically uses the HUMS RR output from the flight alongside pilot declaration and fleet data to provide usage data along with reliability factors.

Once the damage has been noted and compared to fatigue levels by CWC standards, the remaining useful life of the same can be calculated by a simple arithmetic process.

Estimated Run time (ERT) = Fatigue Life Expended

Remaining Useful Life (RUL) = Available RUL - ERT

This process ensures that the life of a component is not based on periodic guidelines but on a usage based spectrum.

**<u>4.d.(iii) Failure Identification and Isolation:</u>**

Once the vehicle is in motion and the sensors are attached appropriately, the next function would be failure identification and isolation. This implies that the system will have to identify the occurrence of an event or the change of output from a sensor (or group of sensors) refers to a failure mode detected. This can be done through condition monitoring techniques (to be explained below) such as time, frequency or time-frequency domain analysis. Once the incipient fault has been detected, the next step would then be to isolate the exact location of the same.

This information would assist the system in predicting possible damage fractions and also alert the maintenance crew at the appropriate time about potential failure. Source isolation, depending on the type of fault and the location of the same can be found through triangulation methods or via clustering algorithms.

**4.d.(iv) Condition Based Monitoring**

For components that face more health concerns on an intrinsic scale condition based monitoring provides the solution to accurately judge RUL's. In this evaluation the system takes condition monitoring results to account and then plan the necessary maintenance action. The purpose of CBM is to eliminate breakdowns and prolong the preventive maintenance intervals [14]. Within the manufacturing industry CBM of critical machine tool components and machining processes is a key factor to increase the availability of the machine tool and achieve a more robust machining process. Thus the CBM system would be expected to utilize information from several sources to facilitate the detection of instabilities in the machining process [15].

Most machinery faults occur on high cycle parts, such as rotary components. For machinery that is used around the clock or production lines where the unexpected breakdown of one part of the production line can shut down the entire plant for maintenance, active monitoring help save time and money. Some of the common identification and analysis tools are vibrational analysis, thermal, acoustic, oil debris analysis, etc.

Vibration:

Vibrational sensing is done by using accelerometers. There are three types of accelerometers that are used: uni-axial (along a single axis), bi-axial (along two separate axis) and tri axial (along three separate axis). Each are placed at critical locations along the airframe to monitor specific components.

For condition monitoring of roller bearings we notice that vibration, temperature, etc is not always the best and only solution to the problem. Vibration monitoring of bearings works only when the vibration energy from other components (shafts, gears, etc.) does not overwhelm the lower energy content from the defective bearings. Usually it is only when the failure progresses the bearing produces audible sound and the temperature rise. If the optimal bearing is chosen and installed properly, then premature damage is usually from improper lubrication or contamination of the lubricant. In this case the vibrations are non-periodic and difficult to detect and interpret.  Similarly vibration analysis of the gears could detect damage after 30% of contact area is pitted [2].

In order to improve the signal-to-noise ratio and make the spectral analysis more effective in mechanical diagnosis, there are specialized techniques like: averaging technique, adaptive noise cancellation technique, envelope detection or the high-frequency resonance technique. Once the noise is filtered out, analysis deals mainly with time-domain, frequency-domain and time-frequency domain methods.

**Time domain**

This mainly deals with waveform statistics like Root Mean Square (RMS), Crest Factor, Kurtosis, etc. Given below is a little more insight into the kind of analysis that time domain methods deal with.

The **Crest factor** is equal to the ratio of a peak value to RMS value of a waveform. The purpose of the crest factor calculation is to give the analyst a quick idea of how much impacting is occurring in a waveform, since impacting is often associated with gear tooth wear, roller bearing wear, or cavitation. In such case it can be more informative method than FFT frequency-domain analysis, since impacts and random noise appear the same in the FFT spectrum, although they mean different things in the context of machinery vibration [2].

**Kurtosis** can be defined as a degree of peakedness of a probability distribution of a waveform. Its application in bearing diagnostics is attractive by the fact that no prior baseline data is needed - kurtosis value greater than 3 is assumed to be an indication of impending failure itself. However, kurtosis value drops down to the acceptable level as damage advances [2].

Frequency Domain

Here the signal is transformed in terms of frequency normally displayed as a spectrum of frequency against amplitude. The advantage over time domain here is to easily identify and isolate certain frequency components of interest. Most widely used is **Fast Fourier Transform (FFT)**. Overall machine vibrations come from multiple component vibration, surrounding machinery and structures. However mechanical faults excite characteristic frequencies for specific fault conditions. Thus nature and severity can be analyzed. Limitations of FFT is that FFT, by definition, is intended for stationary/harmonic signal analysis. So impacts and random noise appear as the same. Another negative is that the information of time is completely lost - it is unknown if the signal fo certain frequency was present all the time or only during certain time periods [2].

**Cepstrum** is another frequency-domain technique that has the ability to detect harmonics and sideband patterns in the FFT spectrum. For example one characteristic common to most vibration signatures of rolling element bearings is that there exist a harmonic series not-synchronized with the shaft speed. These series are fundamental bearing frequencies or rotation rate sidebands that are important in bearing failure diagnosis and are difficult to identify in the spectrum. Because cepstrum has peaks corresponding mainly to the harmonics and sidebands in the signal, they can be more easily identified. This way it is even possible to detect bearing fault without knowing its geometrical parameters by looking for a series of harmonics that are not synchronized with the shaft speed [2].

Envelope technique is primarily used for early detection of faults in rolling element bearings and gearboxes, because the overrolling of a defect shows up in the vibration signal as a high frequency periodic impulsive action that can be easily extracted from a noisy signal by a band-pass filter, rectified and analyzed in frequency-domain. It is an early fault detection technique that can reveal faults in their earliest stages of development, before they are detectable by other vibration analysis techniques [2].

Time-Frequency Domain Analysis:

This addresses limitation of the frequency domain method since each has its own pros and cons. The Short- Time Fourier Transform is an effective tool that overcomes the FFT non-stationary waveform limitations, but, again, it analyzes all the frequencies in a signal with the same window that limits frequency resolution [2].

The wavelet transform is another time frequency domain method that preserves the time information of the original signal and can overcome the resolution problems encountered when analyzing transient signals using Fourier analysis. This has been suggested for analysis of very weak signals, where FFT becomes ineffective, and also has been applied for fault diagnostics of gears, bearings and other mechanical systems [2].

Presently, University of South Carolina's CBM research center is developing a new technique of time-frequency distribution which provides a measure of in-phase and quadrature components of a pair of non-stationary signal.  Since time-frequency analysis is performed on very short time scale signals, it is possible to extract parameters such as instantaneous frequency, group delay and Renyi information [2].

In the example provided by them Fig. 8 shows the scatter plot distribution of the in phase component of the measure on the x-axis and the quadrature component of the measure on the y axis for cases of: (1) balanced and aligned shaft (baseline), (2) unbalanced and aligned shaft, (3)

balanced and misaligned shaft, (4, 5): unbalanced and misaligned shaft.

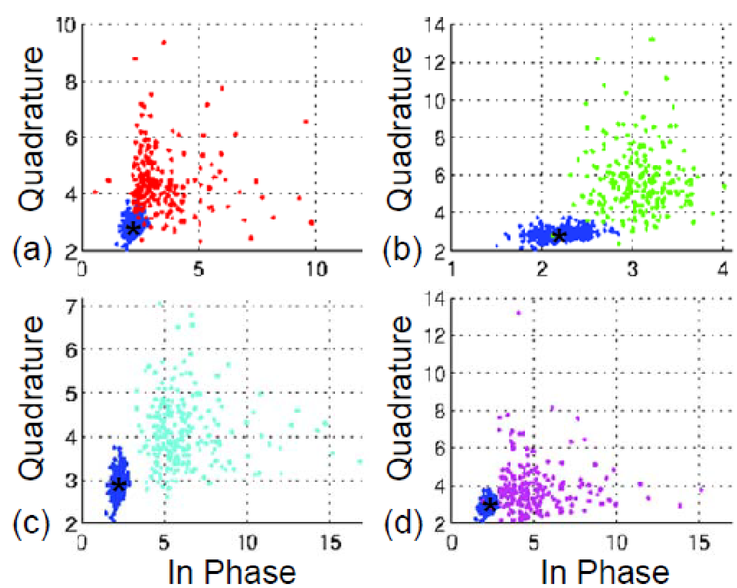


Fig 4 : Baseline Comparisons of the mutual information measure where the baseline distribution (*) is compared to various states of misalignment and unbalance [2].

As a distribution these values can be seen to shift along the x-y plane indicating a shift in part or system status. Differences in this mutual information measure could be further developed into an increased precision statistical indicator of part or system health status [2].

Temperature

Although most of the time temperature sensors are used to encapture bearing health information, this tool can also be used to analyze the environment around thermal critical objects. For a comprehensive system analysis, the HUMS must be able to correlate health activity in relation to immediate environmental characteristics. Temperature concerns also affect the way in which other sensors pick up/produce data.

In bearing temperature monitoring, the temperature rise is significant only after a substantial amount of physical damage has been inflicted on the system. But in the case of improper lubrication, installation, misalignment or overload - temperature rise can be an early sign of impending fault. So bearing temperature monitoring may be useful where loss of lubrication, rather than contact fatigue is the primary failure mechanism.

Electrical Signature Analysis (ESA)

Also referred to as Motor ESA (MESA) or Current Signature Analysis (CSA). Electrical Motor/generator/tachometer current can act as a sensor for detecting electro-mechanical faults in the motor such as rotor bar damage, foundation looseness, static eccentricity, dynamic eccentricity, stator mechanical/electrical faults, defective bearings. As an extension of ESA, this can also be used for motor mechanical drive train diagnostics [2].

Oil Debris and condition Analysis

This method can detect gear box wear even before vibration analysis. This mainly uses two types of sensors: magnetic chip detector and electric chip detector. The magnetic chip detector needs constant inspection, while the electric chip detector provides immediate indication in the cockpit without need an inspection [2].

Acoustic Emission

This is a developing technology that is being used extensively in structural monitoring. Here stress waves that occur inside materials due to crack nucleation/growth, dislocations, phase transformations can be monitored within the range of 100-300kHz. AE signal has its origin in the material itself and not in external geometrical discontinuities. Many problems of AE use are related to parallel sources of AE and temperature variations causing noisy signals.  However this method can detect the growth of surface cracks as opposed to detecting the crack only once it reaches the surface (like the other methods). In the case of roller bearings vibration energy from other components does not affect the AE signal released in the higher frequency range [2].

Limitations are that high frequency energy attenuates very rapidly with increasing distance, hence sensors have to be very close to the source of cracks.

Acousto - Ultrasonics

This uses a frequency range typical of acoustic emission applications. The technique is able to detect and characterize differences in the structure of single and multilayer metallic, ceramic and composite sheet material. This includes corrosion and distributed differences in microstructure and thickness of metals/composites. Here an AU pulser generates low ultrasonic range frequencies which resonate/reflect/transmit and are picked up by a receiver. When damage has occurred to a structure, changes in the signal indicate the type of damage. By calculating the expected changes in the signal from given types and degrees of damage, the damage can be evaluated from AU measurements.
The sensor response and front -end filters remove frequencies below about 100 kHz, which includes most audible noise. Here the arrival time of the signal at different sensors within the sensor matrix, provides an accurate location of the incipient fault/crack. This can provide sensitivities down to a few hundred square micrometers or less.

In the case that the system is unsure of its readings, or crack/fault values fall into a gray zone, acousto-ultrasonics can be utilized to actively detect potential damage to the structural of the aircraft [3].

**4.d.(v) Sensing comparison:**

NDE methods are tabulated relative to their application field, diagnostics potential and width of faults coverage for rotating machinery component monitoring. Figure 5 shows the sensitivity of each sensory system in picking up incipient faults traversing across the equipment of the aircraft with regard to functional failure time.

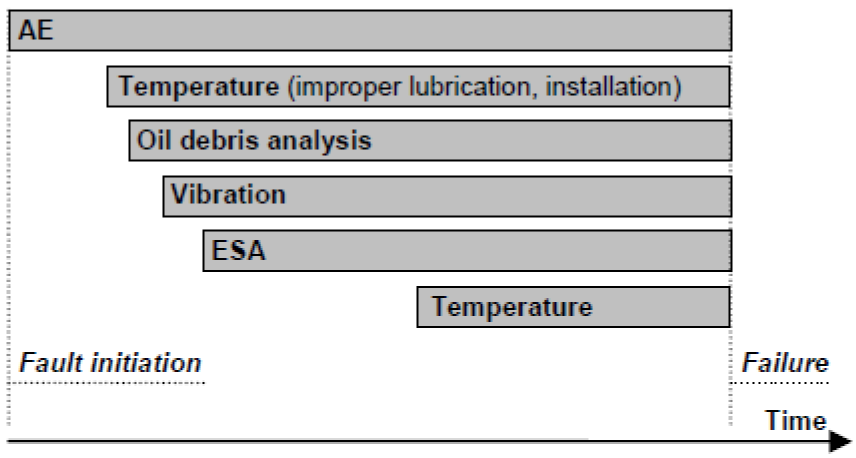


Fig 5 : Fault Sensing Sensitivity [2].

Table 2 shows the application of each sensory module with regard to individual sensory networks in regard to their field of application, diagnostics potential and fault coverage capabilities.

| | Vibration | Temperature | AE | ESA* | Oil debris |
|---|---|---|---|---|---|
| **Fields of application:** | | | | | |
| Science/R&D | • | • | • | • | • |
| Civil engineering structures | • | • | • | | |
| Electrical distribution systems | • | • | | • | |
| Mechanical systems | • | • | • | • | • |
| Electronics | • | • | • | • | |
| Chemical processes | | • | • | | |
| **Usability:** | | | | | |
| Non-destructive | • | • | • | • | • |
| Non-intrusive (■ – thermal imaging) | • | ■ | | • | |
| Online monitoring | • | • | • | • | • |
| **Diagnostics potential:** | | | | | |
| Proven real life applications | • | • | • | • | • |
| Fault detection | • | • | • | • | • |
| Fault isolation | • | • | • | • | • |
| Fault identification | • | ■ | • | • | • |
| Early fault detection (1 – best) | 2 | 4 | 1 | 3 | 2 |
| Monitoring of low frequency (< 0.1Hz) processes | | • | • | | • |
| Sensitivity to mechanical interference | • | | • | • | |
| Complexity of data analysis (1 – highest) | 1 | 3 | 1 | 1 | 2 |
| Hardware cost | 1 | 4 | 2 | 3 | 1 |
| **Faults coverage ( ○ - low sensitivity):** | | | | | |
| Crack initiation or propagation | • | | • | | |
| Gear defects | • | ○ | ○ | ○ | • |
| Roller bearing defects | • | ○ | • | ○ | |
| Friction/lubrication | ○ | • | • | | • |
| Unbalance | • | | | • | |
| Misalignment | • | ○ | | • | |
| Belt drive problems | • | • | | • | |
| Cavitation | ○ | | • | | |
| * – In context of ESA measurements made on generator or tachometer connected to mechanical drive train. | | | | | |

| | Vibration | Temperature | AE | ESA* |
|---|---|---|---|---|
| Typical measurement ranges | 10 Hz – 20kHz | 50 F (10 C) – 300 F (150 C) | 100 kHz – 300 kHz | 20 Hz – 20 kHz |
| Sensor ranges | 0.1 Hz – 100 kHz | -328 F (-200 C) – 2282 F (1250 C) | 20 Hz – 5 MHz | 0 Hz – 100 kHz |

Table 2 : Sensor Application Comparison [2].

# 4.e HUMS Prognostics

To conduct fault prognosis and maximize uptime of the failing component, we must determine impending or incipient failure conditions via condition indicators (CI's). All possible data, historical, experimental and fresh data must be analyzed to set threshold limits and establish probability distributions for enabling methods like weighted voting, Bayesian Inference or Support Vector Machine.

For clustered data points, the first task is to carry out a statistical study of the signature clustering to determine bounds of baseline, misalignments, and load errors.

Support Vector Machine (SVM):

This is a statistical learning theory used in classification, regression and density estimation. SVM maps the input patterns into a higher dimensional feature space through nonlinear mapping chosen a priori. A linear classification surface is then constructed in this high dimensional feature space(basically a hyperplane is defined that separates two clustered data sets). Training the SVM is a quadratic optimization problem. The construction of a hyperplane wx+b=0 (w is the vector of hyperplane coefficients and b is a bias term)., so that the margin between the hyperplane and the nearest point is maximized, can be posed as the quadratic optimization problem [2].

Hidden Markov Models (HMM):

This method is can be used to predict the outcome of a model, based on information from previous instances of occurrence. It can decode an observation with unknown machine condition for fault classification [7].

Rule Based Fusion Method

This is a superset of voting fusion and weighted voting decision fusion techniques. Here weights are assigned to sensors/CI's based on their prior reliability models at detecting a certain fault [2].

Normalization by Min-max

Here normalized CI values are input parameters, so that fault severity is represented. Normalization can be applied by min-max function:

A[i,j] = (CIij - CImin)/(CImax - CImin) [2]

This way a parallel fusion approach to Bayesian inference can be taken

Bayesian Inference

This is supposed to yield an "inverse probability", or probability of the "cause" F (a fault), on the basis of the observed "effect" S (sensor reading/feature). Here P(F) is the a priori, P(F|S) is the conditional probability of the cause F. Bayesian inference assumes that a set of S mutually exclusive (and exhaustive) hypotheses or outcomes exists to explain a given situation. In the decision-level fusion problem Bayesian inference is implemented as follows: a system exists with N sensors that provide decisions on membership to one of S possible classes. The Bayesian fusion structure uses a priori information on the probability that a particular hypothesis exists and the likelihood that a particular sensor is able to classify the

data to the correct hypothesis. The inputs to the structure are P(Fj) – the a priori probabilities that object j exists (or equivalently that a fault condition exists), P(Sk,i|Fj) - the likelihood that each sensor k will classify the data as belonging to any one of the S hypotheses, and Sk the input decisions from the K sensors [2].

$$P\left(F_j \middle| S_1,\ldots,S_K\right)=\frac{P(F_j)\prod_{k=1}^{K}P\left(S_k \middle| F_j\right)}{\sum_{i=1}^{N}P(F_j)\prod_{k=1}^{K}P\left(S_k \middle| F_j\right)}\;.$$

The fused decision is made based on the maximum probability criteria of the above outcome vector. The basic issue with Bayesian inference is the selection of a priori probabilities and likelihood values. This choice has a significant impact on performance [2].

# 4.f Survivability Analysis

Now with the presence of two types of health monitoring systems it would be important to note that both UBM (event based monitoring) and CBM data are equally important. Sometimes it would be a natural tendency of users to put more emphasis on condition monitoring data and neglect event based data. Or on the flip side acknowledge only event based data as a method of overall reliability analysis which might fit the event data across a time and compare between event probability distributions across a fitted graph for assessing functionality.

The overlooking of event data may result from the erroneous belief that event data are not valuable as long as the condition indicators (or features) seem to be working well in reducing equipment failures. This belief is incorrect since the event data are at least helpful in assessing the performance of current condition indicators (or features), and can even be used either as feedback to the system designer for consideration of system redesign or improvement of condition indicators (or features). The overlooking may also result from the fact that event data collection usually requires manual data entry. Once a human is involved, everything becomes more complicated and error-prone. A solution might be to implement and automate event data collection and reporting in the maintenance information system [7].

The model being proposed here would be to integrate both UBM and CBM data as a basis of maintenance decision support. Here  time dependent proportional hazards model (PHM). Introduced by Dr. Cox this model was developed in order to estimate the effects of different covariates influencing times-to-failure of a system. Since introduction this model has been popularly used within the medical and biomedical community to realize hazard rates of a drug based on correlating factors (covariates). This further can be used to analyze both event and condition monitoring data.

A time-dependent PHM has a hazard function of the form

$$h(t) = h_0(t) * exp( \beta_1 x_1(t) + \beta_2 x_2(t) + ..... + \beta_p x_p(t))$$

Here $h_0(t)$ is the baseline hazard function while $x_1(t), x_2(t), ..., x_p(t)$ are covariates in functions of time with $\beta$'s as coefficients. The baseline function can be in a parametric or non-parametric form. Most commonly however parametric baseline functions would be Weibull hazard functions. In this case then a it would be called a Weibull PHM. The covariates can be condition variables such as health indicators and condition features collected from usage and diagnostic data. Maximum likelihood estimation is usually used to build a PHM from event data and condition monitoring data. Modelling a PHM is more or less like the process of regress analysis: a set of significant covariates is finally found and only these significant covariates are included in the model [7]. Once the effects of the covariates on the hazard signal is identified, a Markov model can be used to identify the est time for replacement. The Markov model or a Markov Chain transition probability matrix basically shows the possibility of going from one stage of the failure process to the next, thus alleviating the prediction capabilities for replacement [16].

To break it down the events can be an aircraft taking a higher than 45 degree bank at a certain threshold velocity for given environmental characteristics - usage based data. Say that there are microfractures in the structures which are picked up by acoustic or acoustic-ultrasonic sensors - condition based data. The PHM model would then be able to predict the hazard rate of the micro-fracture (till point of extensive damage) based on usage data and a hazard baseline function. From here on the Markov model (or hidden Markov model based on circumstantial analysis) can be used to predict the possibility of conversion of the fracture from one state of health to the next. Based on this probability then maintenance can be scheduled. Since all of this process is expected to be automated, the system will pull up a red flag for the maintenance staff only once the probability of a "healthy" state of the component/structure reaches a "maintenance required" state based on predetermined threshold.

Therefore I believe that this form of survival analysis integrating the use of both UBM and CBM data to optimize prediction of health needs would be a key area of focus in the development of efficient HUMS systems. However research into this field would require a higher level of research depth and resource assimilation which is beyond the scope of this thesis.

# 4.g Follow Through

Once the diagnostic data has been processed and assessed for ground staff usage, a viable software platform must be established for the ground staff. Since we should assume that not all ground staff personnel are fully trained to understand the working of every aspect of the unit under surveillance. A final output method must be prepared to alert the crew about necessary repair/maintenance checks, where and what form of damage to expect. Also it should be able to provide a directly link to the section of the technical manual they will need to refer to, in order to perform the task to optimal standards.

On the other hand, prognostic data can be used to reinitialize threshold values based on most recent data and can be uploaded to a server/storage-sharing unit for archive purposes. This can also provide the fleet operator, the OEM and the Asset management team the insight that they need to know about either one particular unit or for the entire fleet of units. The best solution to this would be to provide access through a secured internet channel.

However on the more predictive side, the information from the survivability analysis completed, can be used to automatically order parts as per requirement to the necessary maintenance depots ensuring a just in time operation and reducing inventory costs held by the fleet operator.

# 5. Conclusion

The aim of this thesis was to disprove the statement that combination of technology and systems placed over a system to monitor its usage and condition will not help in providing improved maintenance capabilities by providing reduced downtime, and reduced use of resources.

Over the pages of the thesis we can fairly establish that a robust system placed in check of monitoring health and usage would not only provide improved maintenance capabilities by providing reduced downtime but can also provide a much needed safety margin. The HUMS system will be able to monitor through diagnostics the present condition of mission critical components keeping staff and crew aware of the potential usage output of the same. This in turn is a huge step as opposed to assuming that nothing extensive occurred to an unchecked part in between maintenance periods.

In this thesis I then aim to layout an anatomical structure to establishing a HUMS system on a vehicle/unit. This includes identifying the mission critical components that require monitoring through FHA and FMECA analysis and prioritizing them based on criticality of potential failures. Once this is identified, a sensor network can be placed on and around the failure zones so as to enable the system to automatically monitor the well-being of the region through selective or continuous evaluation.

However depending on the unit used (static or dynamic), Usage based maintenance and Condition Based monitoring has been acknowledged so as to leave no stone unturned. On the side of UBM RR algorithms are suggested so as to map the usage spectrum towards predetermined high fatigue maneuvers so as to track the damage infliction based on fatigue charts and CWC data. However if the usage of the unit was not as extreme as the OEM's CWC chart, there would be additional life for the product past the designated replacement time. This way the part can be utilized till its optimal usage point, saving money and labor costs.

However for components whose health are not extensively dependent on the overall usage spectrum but vary on a more intrinsic scale such as bearing in rotary unit, gear tooth chipping a more in depth condition monitoring will be called for. Condition monitoring is then a very versatile field involving the use of vibrational sensors, accelerometers, oil debri analysis tools, acoustic emission sensors, thermographic sensors, etc. For each sensor then diagnostic data can be analyzed (onboard and via ground station centers) from the analog data provided to accurately archive the present condition of the unit. Depending on the criticality of failure, redundant systems will have to be placed to account for unexpected HUMS failures.

From the diagnostic knowledge that we then calculate through various algorithms, data can be compared to fleet threshold data or in relation to trend fitting curves to predict the failure possibilities of each component. This method is very useful in knowing the remaining useful life of the component and helps identify items that need maintenance or repairs. It also keeps the maintenance crew alert for the kind of repairs that will be coming up, ensuring proper equipment availability with the luxury of a lean inventory.

Now through the use of UBM and CBM the health of the overall system/unit can be judged based on usage and condition, but these two factors are obviously interdependent. Here I propose the use of a survivability tool to analyze the impact on the hazard rate based on usage (event) and conditional data. Using the data available to form a more efficient maintenance aid that can predict accurately the failure potential and the probabilistic trend for the same.

Subsequently the information that was generated can provide a lot of use, allowing better predictive maintenance capabilities, higher safety margins on unit usage, lower resource utilization, reduced downtime, lower cost, etc. Here then we can establish that the use of technology to evaluate the health of a system would definitely provide a higher awareness of its capabilities and allow a team to plan ahead for the future.

With the need of higher efficiency levels, the need for lowering operational costs and higher confidence and reliability levels, HUMS will soon become an essential necessity by international standard. Administrative organizations like the Federal Aviation Authority has been evaluating the present technology available for the same in hopes of establishing a compulsory standard on fleet operators. Eventually this trend will trickle down to other fields of operation as well, be it the transportation aspect of application or civil. HUMS systems provide a higher confidence level of knowing exactly what is happening with the system and that knowledge will provide the cushion of trust for the user.

This field is still in need of a lot more research, but will the increasing trend of academic and industrial effort going into it, a HUMS system would soon be a very daily implication of our usage.

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