Lessons Learned from Rotary- and Fixed-Wing HUMS Applications

Diagnostics, Prognostics and Health Management on Aerospace Platforms
Integrated Health Management Systems

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Abstract - The United States Navy, United States Marine Corp, United States Army and their supporting aircraft manufacturers have teamed with BFGoodrich Aerospace Aircraft Integrated Systems (AIS) Division to develop an integrated Health and Usage Management Systems (HUMS) for their service-specific helicopters. Primarily, these aircraft include H-60 and H-53 variants. Likewise, Lockheed-Martin has contracted with AIS to demonstrate a propulsion system Prognostics and Health Manager (PHM) for use on their lift-fan equipped Joint Strike Fighter (JSF) Preferred Weapon System Concept (PWSC) aircraft. The principal intent is to improve readiness and reduce operational costs using streamlined maintenance practices. The enabling data will be derived through automated condition and health monitoring. Although each HUMS user requires different aircraft- and service-specific functions, the experience of providing these advanced services to a variety of customers enables us to better define those functions and their integration (both on-board and off). This paper presents lessons-learned from several aspects of aerospace HUMS (diagnostics, prognostics and regime recognition) implementations and touches on related areas (conceptual design, system integration, etc.) as needed. These lessons are based on our continuing work with military platform users and designers while making new technology applications available through the open system architecture.

Overview – The general philosophy for HUMS is well understood and has been widely accepted [1]. However, the requirements for complex HUMS continue to evolve due to maturing customer expectations and sensor and signal processing advances. This evolution is common for a product that is being jointly designed with a customer. Furthermore, HUMS utilizes both matured and maturing technologies and therefore it is sometimes difficult for the designer/customer to specify detailed requirements. This difficulty is compounded by the fact that, although HUMS contains a set of generic functionality that is platform independent, configuration and interpretation of data is quite platform specific. In short, a HUMS that works well on one platform does not readily lend itself to easy application on a different platform. Significant effort must be added to accommodate HUMS data analysis and re-application to the new platform. Given these conditions, a more dynamic requirement discovery and systems engineering process is appropriate. As an example, Bahill and Gissing described a framework of such new process in their paper [2]. This new process incorporates a feedback loop at each phase of productization as opposed to the conventional rigid process that has only a limited number of feedback loops. This allows customer and provider to discover/re-evaluate/modify requirements in a timely manner and reduces major rework on the requirements after entering the product development process. Such a process, though must be complemented by advanced data acquisition, signal processing and databasing in order to produce the customer's desired services.

This paper considers the advanced data acquisition, signal processing and databasing aspects and is organized into sections as follows; System Concept Design, Usage Monitoring, Mechanical Diagnostic and Prognostic Algorithm Development, Rotor Tuning (Helicopter-Specific) and Data Acquisition and Management. Each of these major functional areas must be optimized independently (to obtain a high degree of efficiency in performing each function) but also as a whole to fulfill the expectations of the advanced HUMS user. As in any highly technical (and intellectual) a pursuit as HUMS, the end user and HUMS provider, working closely with the component/system manufacturers must share a common vision and communicate effectively to achieve their goals. Each section will conclude with specific lessons learned that are common to any HUMS application regardless of the platform.

System Concept Design – The conceptual design of any useful system begins with the customer's (documented) requirement statement. Clarity, precise wording and mutual understanding are each paramount through the entire HUMS implementation. Lacking these, the system concept will be different in the minds of the customer and provider and the delivered system will appear to not provide its required functions. One key to success throughout the entire implementation is to maintain a clear distinction between what the system is required to do and how that requirement is to be fulfilled. Confusing the two can lead to fixation on how the system is to fulfill the requirement at the expense of accomplishing principal requirements. For example, lowering maintenance costs is a principal requirement in the Integrated Mechanical Diagnostics (IMD) Commercial Operations and Support Savings Initiative (COSSI) example. Since deriving the information needed to optimize maintenance procedures is computationally intensive and administratively complex, there are many forces at work to deny achievement of that principal requirement. However, this is an achievable pursuit as proven by several successful HUMS implementations in both Europe and the United States.

Fortunately, the requirement for most HUMS can be stated rather concisely; Provide the information needed to maintain the platform at the lowest maintenance cost commensurate with the required degree of operational readiness or safety. To do this, the HUMS must acquire the data needed to execute the diagnostic and prognostic algorithms that will describe the immediate and expected mechanical condition of the platform components being monitored. It must also determine the component's current and trended (historical) condition and store the data relating their response(s) to the conditions under which the data was obtained. There are two corollaries to these requirements. The HUMS must be able to correlate sensor data with the physical condition of the monitored component(s). It must also be able to access historical data for use in determining (by direct comparison) the relative "goodness" of proposed diagnostic and prognostic algorithms with respect to the maintenance actions that they subsequently mandate.

Entwined in the paragraph above is the combination of what the system must do and how it will do it. It must enable the lowest-cost maintenance procedures commensurate with the required degree of operational availability and flight safety. It will enable this by allowing efficient (automated) processing (and re-processing) of a growing data library using advanced algorithms optimized to accomplish one of a variety of goals. The data library must include a maintenance history for each HUMS-fitted platform, the "cost" of each maintenance action and the ability to correlate maintenance actions with HUMS indicators.

<u>Lessons Learned</u>

Maintain constant focus on the overall goal of lowering the platform user's maintenance cost while improving operational readiness and safety. Lower operational cost benefits the user in obvious ways and keeps the manufacturer competitive. Each participant "wins".

Strive to distinguish between what the system is required to do and how the system is to accomplish the goal. What the system does is correlate data from diverse sources (Original Equipment Manufacturer (OEM) sensors, pilot input, aircraft "state" parameters, HUMS-specific accelerometers and sensors, aircraft configuration data, maintenance histories, etc.) in order to allow platform maintainers and designers to optimize operational costs given various constraints. The "how" part is accomplished by efficiently acquiring and manipulating that diverse data for use in advanced algorithms (functions). Indeed, the results of many of the calculations serve only as input for subsequent calculations or "higher-level" functions.

Develop and execute the data acquisition and reduction functions as efficiently as possible. This will provide the best chance of delivering the HUMS to the customer(s) who developed the original requirements. HUMS applications are sometimes so complex that turnover in the personnel who are developing the system (customer and HUMS provider alike) hinders progress.

Providing the HUMS only signals the start of maintenance practice optimization. The ease with which the HUMS provides the data needed by the maintainers and operators to optimize their processes is only an enabler – not an end goal.

Usage Monitoring – Usage monitoring is a key part of any complete HUMS as this function automates recording the platform's actual usage. Usage monitoring is most often applied to life-limited parts subjected to low frequency vibration [3]. One to twenty hertz data capture is currently deemed sufficient to capture usage parameters (bank angle, roll rate, pilot input...) as well as recor complex maneuvers (control input reversal, severe pull ups...). Automated recording frees the pilot of the burde of recording any usage parameters. He or she can bette concentrate on the mission. Likewise, the automat monitoring determines the actual time spent in the mos damaging regimes (those that consume the most useful lif from flight critical components) either during norm (heavy) use or emergency actions. Thus, automated monitoring captures the information needed to determine parts life consumption at the times when the pilot is least likely able to accurately determine the time spent in those damaging regimes. From a design perspective, the intent is to capture the highest rate data while the aircraft is experiencing the most dramatic maneuvers. To accomplish this, the HUMS automatically captures usage data at a high rate (up to 20 Hz in this example) on a continuous basis, determines the recent (previous few seconds) regime sequence and records the high-rate data if maneuvers are complex. Otherwise, the data is averaged over a longer period of time (second(s)) and the average value of the given parameter is stored. Thus, data storage is minimized when the aircraft is flown with minimal control input. Furthermore, parameters that do not require high sample rates (altitude, for example) can be configured to be acquired at the lower rates.

Current approaches to usage monitoring involve defining the flight regimes to the greatest extent possible. There are two principal reasons for this. First, so that one can determine the actual time spent in the most damaging regimes. Second, so that one can reduce the amount of flight time designated as "unrecognizable" as this time is conservatively burdened by the highest usage factors. (Note; Parts lives are defined today based on a set of worst case composite usage spectrum. This practice provides a high degree of reliability by adding conservatism).

Driving maintenance costs down surfaces the need to be able to reprocess the flight data associated with regime recognition. Improving regime recognition techniques presents the opportunity to derive maintenance cost savings from previous flight operations in which less precise methods arbitrarily lumped unrecognizable flight time into the most conservative (high usage factor) regimes. Expended parts life can be more accurately calculated through the continuing refinement of improved regime recognition parameters. Likewise, the ability to correlate flight history data with maintenance histories and planned maintenance actions is the key enabler for improving maintenance processes. The critical HUMS contribution is the ability to acquire usage data and automate its analysis.

The complement to regime recognition is component parts life decrementing based on the regimes flown. Many components are monitored. Each component has one or more failure modes. Damage accruing to each component (per each failure mode by each regime) must be computed individually.

This sum of individual damages (TotalDamage) is a fraction of the parts lifetime toward a particular failure mode, but includes damage from all regimes. This value for TotalDamage will also start at zero for a new part, progress through the fractions at various rates depending on the regimes to which it is subjected, and arrive at 1 at the end of its expected life (time to retire part).

The TotalDamage is used to compute the projected retirement time (PRT) according to the following equation:

$$PRT = \frac{TotalTime}{TotalDamage}$$

The TotalTime in the equation represents the up-to-date total operational time experienced by the part. The TotalDamage is the up-to-date damage received by the part toward a particular failure mode. PRT provides a projection of the lifetime of the part at any given point in time, based on the regimes to which it has been subjected. For example, component A, a Main Rotor Hub Assembly, has a life expectancy of 10,000 hours when subjected to the assumed distribution of flight regimes. Figure 1 below shows this expected use for the life of this part.

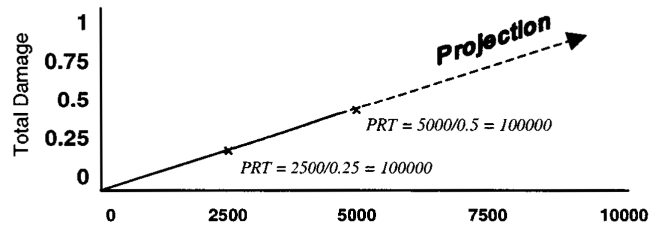

Figure 1: Projected Retirement Time for Expected Use

The PRT projection taken at any point will always produce the expected lifetime of ten thousand hours.

In actuality, helicopters fly many different regimes at different times. The resulting data projects a retirement time as shown in Figure 2 below. Once again it is clear that the PRT calculation produces a retirement time based on the regimes that the component has undergone up to that point.

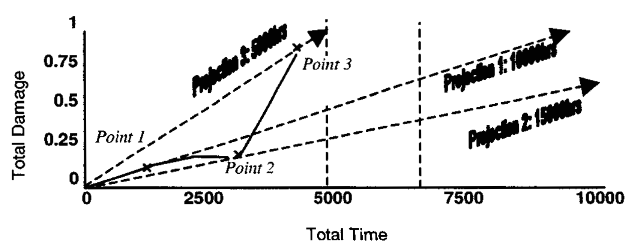

Figure 2: Projected Retirement Time for Variable Use

When operational time is not tracked by the HUM system, a modified equation is used:

$$PRT = \frac{TotalTrackedTime}{TotalTrackedDamage} + \frac{TotalUnTrackedTime}{TotalDefaultDamage}$$

Note that the up-to-date usage time can be easily calculated based on PRT, Total Damage and Calculated Retirement Time (CRT) provided by the manufacturer.

Based on the above description, PRT is calculated based on the aggregate damages from all regimes. Since PRT is a projection of current trends into the future, it can be quite sensitive to helicopter usage in the early stages of HUMS implementation. The earlier in the part's lifetime the PRT is calculated, the further the resulting trend has to be projected. Therefore, for a new part that has only received a few operational hours, the computed PRT may be highly biased. As the part gains flight time, the PRT calculation gains "credibility", becoming more and more accurate as the part retirement time approaches.

Lessons Learned

Automated Usage Monitoring frees the pilot from administrative cockpit tasks and promises more accurate recording of the time spent in damaging regimes. Accurate reporting of the distribution and duration of regimes flown is important in order to determine the amount of "life" time to decrement from life-limited parts.

Reprocessing regime data with more accurate regime definitions offers the potential to reclaim spent life while maintaining high flight safety standards and extending the time period between maintenance actions for life-limited parts subject to low frequency vibration. This is because high usage factors are usually assigned to all regimes within the flight sequence that are denoted as "unrecognized".

The transition from a fleet of non-HUMS equipped aircraft to fleet-wide implementation will require the aircraft operators to determine the life already decremented from a component based on previous operations. This will become the starting point from which subsequent life will be decremented from the component as determined by the HUMS. Advanced condition assessment techniques (direct physical observation) coupled with HUMS-derived component degradation data will permit spent life to be accurately determined through physical inspection. Test cell data or laboratory determinations will validate degradation rates.

Insight gained from tracking the actual usage of individual helicopters will permit maintainers and operators alike to schedule the aircraft for maintenance activities and certain missions based on the known condition of the helicopter's components.

Mechanical Diagnostic and Prognostic Algorithm Development – Mechanical Diagnostic and Prognostic algorithms are the basic enablers of HUMS functionality. They are the key ingredients that will enable transition from time-based to Condition-Based maintenance and, eventually, Just-in-Time maintenance. Generally speaking, diagnostic algorithms provide a snapshot of an individual component's current condition. To accomplish this, diagnostic algorithms are usually applied to the high frequency vibration signal acquired from an accelerometer mounted near the signal source. Advanced analog or digital signal processing provides the power spectral density of the accelerometer's output. The signal amplitude at a given frequency (that frequency being related to some physical occurrence such as gear meshing or shaft rotational speed) being indicative of the component's mechanical condition. Condition Indicators (CIs) are derived by correlating one (or more) signal amplitude(s) with the amplitudes obtained by operating with known worn or faulted parts. Knowing how that amplitude varies depending on the component's physical condition provides a measure of the component's relative condition as it deteriorates from new to worn conditions. The signal amplitude obtained from a deteriorated part is used to set acceptable thresholds for safe component operation. As long as the signal amplitude remains below the preset thresholds, the component is considered to be safe for continued operation. Combining these CIs in a somewhat artful manner (called nonlinear mapping) allows the analyst to determine the most accurate measure of a given component's health. The resulting value is called a Health Indicator, or HI. As with CIs, HIs provide a relative measure of the component's health whe compared to the HI of a known faulted part. The warnin and alarm thresholds for these indicators are set to insur continuing safety of flight and sufficient time to pla routine maintenance functions. Exceeding these indicat thresholds is the trigger for planning some predetermine maintenance activity, usually inspection or replacemen Thus, accurately defining the warning and ala thresholds for component HIs has great bearing on t system's operational safety and future maintenan requirements. Specifying these values determines t extent of maintenance that the aircraft operator must accept in order to maintain a desired level of flight safe

Relying on diagnostic indicators alone, however, is only a partial step towards condition-based maintenance.

A prognostic function provides the ability to determine if a trend is developing in HIs for a given component. A more aggressive definition of prognostics includes the ability to determine how quickly that indicator is approaching (or might cross) a preset threshold. Like setting diagnostic indicators, prognostic trending requires a sufficiently large set of examples to exist and be analyzed before one can confidently use the resulting prognostic function. Accurate prognostic functions will exist for a specific aircraft component only when a statistically sufficient number of faulted conditions have been recorded (captured in the data), analyzed and correlated with the physical condition of the component in question. Refer to "Prognostics, The Real Issues Involved With Predicting Life Remaining" (Engel, Gilmartin, Bongort and Hess, contained within these proceedings), for a more detailed prognostics discussion.

Thus, the pursuit of advanced diagnostics and prognostics presents a dilemma to the commercial and military aviation communities. Historically, suspected faulty parts are inspected and/or removed from operational use to maintain conservatively high safety margins - expensive but considered worth it. However, shrinking budgets and high maintenance costs have driven owner/operators towards determining the current (diagnostics) and expected (prognostics) condition of aircraft components so as to be able to fly safely with slightly worn components. As with diagnostic indicators, specifying prognostic indicators has a significant effect on the maintenance actions needed to maintain a given level of flight safety because these values also determine the extent of maintenance that the aircraft operator must accept in order to maintain a desired level of flight safety.

As mentioned previously, component health evaluation provides a composite assessment of the overall health of each individual drive train component based on calculated diagnostic indicators from designated sensors. Generally speaking, the relationship between the diagnostic indicators and the faults is not straightforward. Furthermore, especially when mounting a HUMS on an aging platform, the relationships are not well understood. Therefore, the health evaluation algorithm must have the ability to account for this embedded uncertainty. Two candidate algorithms, which are designed to cope with uncertainty, take an array of previously calculated indicator values from various diagnostic algorithms as inputs and produce a composite indicator of health for each component in a single acquisition (time-sliced). Two algorithms are discussed in this paper. They are based on probability and fuzzy logic respectively [4] [5]. Neural networking algorithms are equally applicable but not considered in this paper as there is currently insufficient data available to perform feature mapping and pattern recognition with confidence yet.

Probabilistic Algorithm. This algorithm is based on the assumption that the probability density function (p.d.f.) of the "results" produced by each individual diagnostic algorithm (i.e., diagnostic indicator values) is a normal distribution when the monitored component is healthy (i.e., no fault). One can then establish a threshold based on the percentile of the distribution. For example, if we choose to use the 99.95 percentile of the distribution as the threshold for differentiating normality and anomaly, then the threshold value can be calculated according to:

$$T = \mu + CV * \sigma$$

where T is the calculated threshold value based on the 99.95 percentile (with a critical value of 3.27) of the normal p.d.f., μ and σ denote the mean and the standard deviation of the distribution, respectively. Note that the specific indicator must somewhat increase along the positive direction when a fault occurs. If the 99.95 percentile is used, we can expect that only 0.05 percent of the calculated diagnostic indicator values will be greater than the threshold value when the monitored component is healthy. In other words, the probability of producing a false alarm or missed detection based on this indicator is 0.0005.

Data needed to set baseline indicator thresholds should be acquired and processed under a set of flight regimes that produce compatible characteristics for the monitored components. An example flight regime looks like: 80% < transmission torque < 100% @ steady heading, straight and level flight. The selected baseline data sets must be free from any known drive train faults and/or sensor faults in order to obtain a set of clean and reliable thresholds for the subsequent evaluation. Furthermore, one needs at least 30 or more data sets to establish the baseline thresholds to be statistically significant. Once we have the computed compound fault probabilities from individual sensors, we can then calculate the component fault index (CFI) with a weighted average formula where N represent the total number of sensors used for a specific component. Obviously, the largest weight is assigned to the primary sensor (i.e., P_1^f) and so on, according to the fault sensitivity of each individual sensor. Also note that $CFI \in [0, 1]$: when $CFI \to 1$ means the component is most likely faulty and when $CFI \rightarrow 0$ means the component is most likely healthy.

Trend Analysis. The obtained "time-sliced" CFIs for individual components should be saved and trended on the ground based system for further evaluation. A positive increase of a CFI may indicate a developing fault because it suggests an increase of fault likelihood. The trend (temporal information not described in this document) may be incorporated into a higher level of component health evaluation.

Cross Sensor Fusion. The algorithm described above is primarily used in combining indicators obtained from accelerometers. Results from other types of measurement such as transmission torque, chip detector, gearbox oil temperature can also be combined with the same algorithm or with a fault-tree type expert system. The cross sensor fusion approach is not described in this document.

Fuzzy Logic Algorithm - This section outlines a component health evaluation methodology based on fuzzy logic. Fuzzy logic provides a more flexible way to quantify uncertainty than probability theory as the probabilistic process model has to be derived based on strict rules. The concept behind the fuzzy logic methodology is relatively simple. Each diagnostic indicator is given a fuzzy Membership Function (MF) pairing (input and output functions) that represents the distribution of uncertainty associated with this particular diagnostic indicator. Possible MF includes Normal Distribution, Z Distribution, S Distribution, Triangular Distribution, etc. The values of individual diagnostic indicators are then mapped to fuzzy numbers with the corresponding MFs. The set of fuzzy numbers are then combined with fuzzy operators to produce an interim number which is then de-fuzzified to produce the final answer.
Figure 3 below (example) shows the SO1 overall scheme.

Fault Declaration - The obtained fuzzy CFI can be interpreted as follows:

- Healthy: CFI < 0.33
- Warning: 0.33 ≤ CFI < 0.67
- Alarm: 0.67 ≤ CFI

For components which have multiple CFIs such as shafts and bearings, a fault is declared if any one of the CFIs exceeds its limit. For example, if the SO1 CFI of a certain shaft exceeds 0.33, a shaft imbalance fault warning is declared. For bearings when any of the CE, BSE, IRE, or ORE, or General CFI exceeds 0.33, a specific and/or general bearing fault warning is issued. Updating reference values, cross-sensor signal fusion and trend analyses are conducted in the same manner as with probabilistic algorithms.

Lessons Learned

The key to enabling advanced mechanical diagnostic and prognostic functions is a data analysis and reduction system that is automated to the greatest degree attainable. This is true even for modestly sized fleets (small fixed-base operators). The automated system must permit an analyst to introduce new algorithms and thresholds (warning or alarm). It must also provide the ability to reprocess historical data using those new algorithms and thresholds. Short of this, the analysts will be overwhelmed by the amount of data to be processed and will not even be able to establish a baseline set of diagnostic and prognostic functions to improve upon.

The aircraft operator and equipment manufacturer must work closely to set the warning and alarm thresholds such that the operator can maintain the desired safety of flight within the maintenance expense constraint. The historical CI and HI data provided by the diagnostic and prognostic functions, associated with the observed

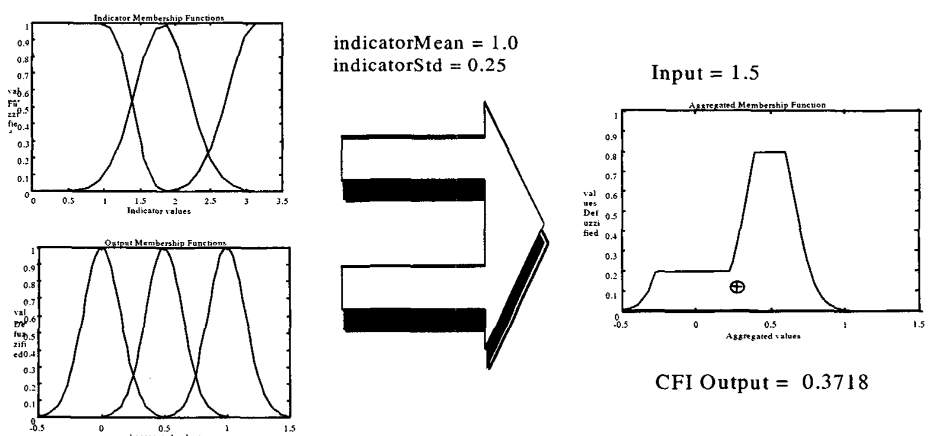

Figure 3. Scheme for Shaft Order 1 Analysis (Example)

physical condition of flight critical components (as documented during maintenance actions) are the critical pieces of data needed to advance to condition-based and subsequently, just-in-time maintenance.

The transition to condition based maintenance will most likely be enabled by using data acquired by destructive component testing. This is because faulted parts are usually (conservatively) removed from an aircraft before a statistically significant amount of data can or will be acquired. Data-intensive destructive testing correlated with scientific observation of the component's deteriorating condition will provide the insight needed to enable on-board prognostic functions with confidence. Destructive testing of "spent" components in a test cell environment is a viable source of data to validate prognostic algorithms. This data will enable the tradeoff studies that will relate component condition with safety of flight and required maintenance. A reasonable number of tests-to-failure are needed to guarantee statistically significant results or to permit the training of neural network algorithms to recognize developing trends.

Rotor Tuning (Helicopter-Specific) – Rotor tuning functions are intended to minimize vibration at specified locations within the cabin (cockpit, passenger compartment, instrumentation platforms) as measured at pre-established events (hover in or out of ground effect, straight and level at 90 knots, etc.). The intent is generally to improve cabin comfort and extend the life of the rotor components (even extend the life of avionics themselves). Likewise, well-balanced main and tail rotors are expected to require less overall maintenance once properly tuned.

The tuning algorithms generally utilize the vibration signal(s) of up to six airframe-mounted accelerometers. The algorithms quantify (and propose adjustments to alter) either track or balance. Tracking functions attempt to minimize the variation of the blade tip height above or below a datum. Balancing functions attempt to minimize main and tail rotor vibration. Although both track variation and balance have (historically) been minimized to provide the smoothest flight conditions, proper balance has now been shown to be the dominating concern. For example, a low-vibration balance solution can exhibit a high degree of track variation. Indeed, adequate balance can be obtained without the need for any track data at all thus simplifying the on-board implementation. One can achieve adequate balance by adjusting a variety of blade (one, or more, trim tabs per blade) or rotor hub (pitch rods, weights, etc.) components.

Herein lies a dilemma; multiple balance solutions (sets of blade and hub adjustments) can all be shown to deliver an expected vibration level that is within acceptable bounds. The problem is to choose the solution that fits within a much broader set of constraints than simply "lowest vibration at point X within the aircraft". For example, one may want to attain the lowest vibration within the passenger cabin at 150 knots straight and level and still have many balance solutions that predict vibration to be lower than an acceptable maximum. This problem is compounded as the number of blades and number of tabs per blade increases. One must then choose whether the absolute least vibration or ease of maintenance is the most important criteria. Again, how one chooses the balance solution to implement is a significant factor in the cost and frequency of the rotor maintenance program. The ability to balance the rotor is insufficient with respect to planning a maintenance program. One must also be able to equate the cost of various rotor maintenance activities with what is deemed an acceptable balance solution and how often the maintenance actions must be performed.

Lessons Learned

A resident (full time) rotor balancing system is currently considered to be the function that has the greatest potential for reducing helicopter operating cost. The ability to acquire rotor tuning related vibration data at any time (within the bounds of pre-defined flight events) precludes the need for mounting special balancing equipment and balance-specific flights. However, the cost savings can easily be diluted in many ways. First, by pursuing the best overall balance attainable (over-maintaining the rotor hub). Second, by frequently changing the location at which you want to achieve low vibration levels. Third by frequently changing the regime in which you want to experience the least vibration. Fourth, by allowing maintainers (with different preferences for how to achieve proper balance) to chose the manner in which they will balance the rotor. Thus, the ability to attain low vibration levels (proper balance) can lead to increased maintenance effort unless the system operators (owners maintainers and HUMS-provider) determine how best to act upon the information provided by the rotor tuning function.

Data Management – Effective data management, in its simplest form, pertains to having efficient access to the information needed for meaningful analysis. Efficient data management allows the analyst to consider any of the available data as factors in developing improved algorithms and processes. Given that there are over ten thousand indicators obtained per flight to characterize drivetrain mechanical condition alone, effective data management is crucial.

The ability to correlate seemingly unrelated data is crucial in this early phase of HUMS deployment. In part, this is due to the analyst's current inability to identify the critical indicators that foretell deteriorating performance. It is also due to the fact that most advanced HUMS functions will be derived from correlating multiple indicators (temperature, pressure, pilot input, vibration signal transients, rigid body motions, etc.) with potential causes for the observed phenomena. For example, a failing rotor blade damper might be associated with a consistent (albeit temporary) lag in track following a distinctive pilot input. Distinctive means that the input can be uniquely identified as occurring with the observed phenomena. Likewise, a transient in the n/rev (n = the number of rotor blades) might be correlated with the blade's lag to clearly indicate the faulty damper. Thus, the presence and degree of damper deterioration might be inferred by integrating data from a variety of sources – none of which involve damper instrumentation.

The same type of data correlation is important when determining (or optimizing) maintenance process effectiveness. However, it's the maintenance records that require adequate and accurate management at this stage. Correlating, over time, the aircraft's state variables (airspeed, power settings,...) with sensor measurements and verified component conditions provides insight into how the usage contributes to parts degradation. In fact, it is correlating the engineering data with the maintenance data (component condition and maintenance history) that will eventually provide the insight needed to optimize a given maintenance procedure.

Lessons Learned

Time spent to correlate and make available data from diverse sources will reward the customer and HUMS developer alike. Incidentally, this speaks (again) to the need to automate data access and the data reduction processes. Access to a wider variety of data allows the analyst to develop solutions based on interpreting already-available information (sometimes precluding the need for any additional sensors). Likewise, using indicators that otherwise do not have a direct relationship with one another gives the analyst confidence that the combined indications truly represent a developing condition.

Initial solutions to customer requirements will typically have to be "brute-forced" before an elegant solution becomes available. Access to disparate data allows the analyst to experiment using various data correlation techniques to determine the most effective indicator combination. In the same manner, knowing the critical indicators (and those that are normally unrelated) allows the analyst to build in safeties against false warnings and alarms. The elegant indicator set and algorithms usually become apparent only after many false starts and extensive reprocessing of the same data.

Conclusions

What seems so often to be mere common sense will distinguish the successful HUMS provider from those who are not capable of meeting their customer's requirements. In fact, it is common sense and adherence to basic business and engineering principles that will transform the current HUMS vision into reality. Understand the physics associated with the platform's mechanical performance. Know (and document) your customer's requirement. Include the pilots, maintainers, analysts, business managers and other stakeholders appropriately during each phase of the development and testing phase. Accept that you will initially have to acquire more data and data from more diverse sources than you expected in order to develop effective solutions. Following this, acquire data selectively and manage it aggressively and in a straightforward manner (including the data you subsequently produce). Automate data reduction and reporting to the greatest extent possible. Automate the ability to reprocess data. Implement the HUMS in a timely manner. These actions wil' dramatically improve the overall probability of success a the customers who originally set the requirements an expectations may still be the ones who accept delivery Continually validate your performance against you customer's documented requirement. Failure to perforn well in any of these areas will invite needless overhead i the development and operational processes and keep th HUMS provider from accomplishing even the most basi goals. Poor performance will limit the HUMS provider t short-term "success". The customer will not achieve the ultimate goal of reducing maintenance costs whil maintaining (or improving) operational readiness an safety. HUMS applications will mature and flourish onl when each of these elements is present.

Clearly, the previous and continuing success of tl IMD COSSI program depends upon our collective abiliti as provider, OEM and (military) customer to mainta effective communications. We must also learn how properly manage the information that will make t

HUMS vision, improved operational readiness coupled with reduced maintenance costs, a reality in the very near future. Automation may well be the enabler, but HUMS implementations will fall short of their goals unless both customer and provider have a clear and common understanding of their requirements and how they will utilize the information the HUMS will provide.

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