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CBM+ for Helicopter Health Management

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ABSTRACT

The basis for Condition Based Maintenance Plus (CBM+) is to allow timely maintenance of complex machinery using technologies for diagnosis and prognosis of faults based on real-time machinery conditions. CBM+ increases mission availability and opportunistic maintenance. It decreases maintenance actions and provides a better logistic footprint. We describe a CBM+ system for real-time condition-based analysis for helicopters. The system described here provides diagnostic and prognostic feedback indicative of helicopter's health status and provides indication of the remaining useful life of the components it is monitoring.

1. INTRODUCTION

The fundamental challenge in CBM+ for helicopters is that they are not stationary since they operate over a large number of regimes or operating conditions. They also operate under constantly changing environmental settings and have to be maintained on an opportunistic basis. These variations increase the complexity of determining the system's behavior, detecting component degradation and predicting remaining useful life for the components being monitored. In the CBM+ system described in this paper, an open architecture is used. It is modular in nature to allow distributed design, development and maintenance of individual modules and to allow collaboration with other systems. The modules have well defined interfaces and functionalities. Algorithms are updated over time to optimize detection and prediction of faults.

2. OVERVIEW

Current maintenance systems for helicopters are reactive, scheduled or opportunistic, i.e., a maintenance action is taken either when a fault occurs, on a predetermined schedule or to take advantage of the resources, efforts and time already dedicated to the maintenance of another part in the system. Maintenance activities themselves can introduce a risk of malfunction, so it is better to perform them only when needed, as much as possible. Also, scheduled maintenance actions taken prematurely often result in underutilization of resources. Hence, both reactive and scheduled maintenance strategies can contribute to an excessive logistics support burden and high operation and support (O&S) costs.

The system described in this paper aims to reduce O&S cost by reducing reactive and scheduled maintenance by accurately assessing helicopter health and predicting failure of critical helicopter components based on actual usage in operation environments. The CBM+ system for helicopter health management described here integrates a set of diagnostic, prognostic and health assessment technologies to achieve its mission. By knowing what components are in need of maintenance and how soon that is required, maintenance actions can be planned in advance based on the remaining useful life of components.

The system gathers signals from a large number of sensors positioned and adapted for measuring a helicopter's health condition. The input signals are conditioned and normalized using signal processing techniques to create features. A collection of condition indicators are derived by pre-processing the inputs and derived features using pattern recognition, data correlation and data mining techniques to determine an optimal subset of signals that best reflects the health of the helicopter. A Self Organizing Map (SOM) is also used for signal conditioning. It helps remove noise from the signals and also reduces higher dimensional inputs to a lower dimension in real time, to determine the operating regime of the helicopter, for use in subsequent processing.

The processed input is then provided to a Fuzzy Adaptive Resonance Theory (Fuzzy ART) neural network. The Fuzzy ART neural network receives the condition indicators as inputs and is able to detect and classify the current operation state of the helicopter as one of the previously known states. The operational health of the helicopter based on the current operating state is provided as an output of the Fuzzy ART neural network. Thus, the neural network serves as the prime detector of helicopter's current health status.

A Bayesian Intelligent Network is adapted to receive a helicopter's state of health (summarized and optimized) from the Fuzzy ART neural network

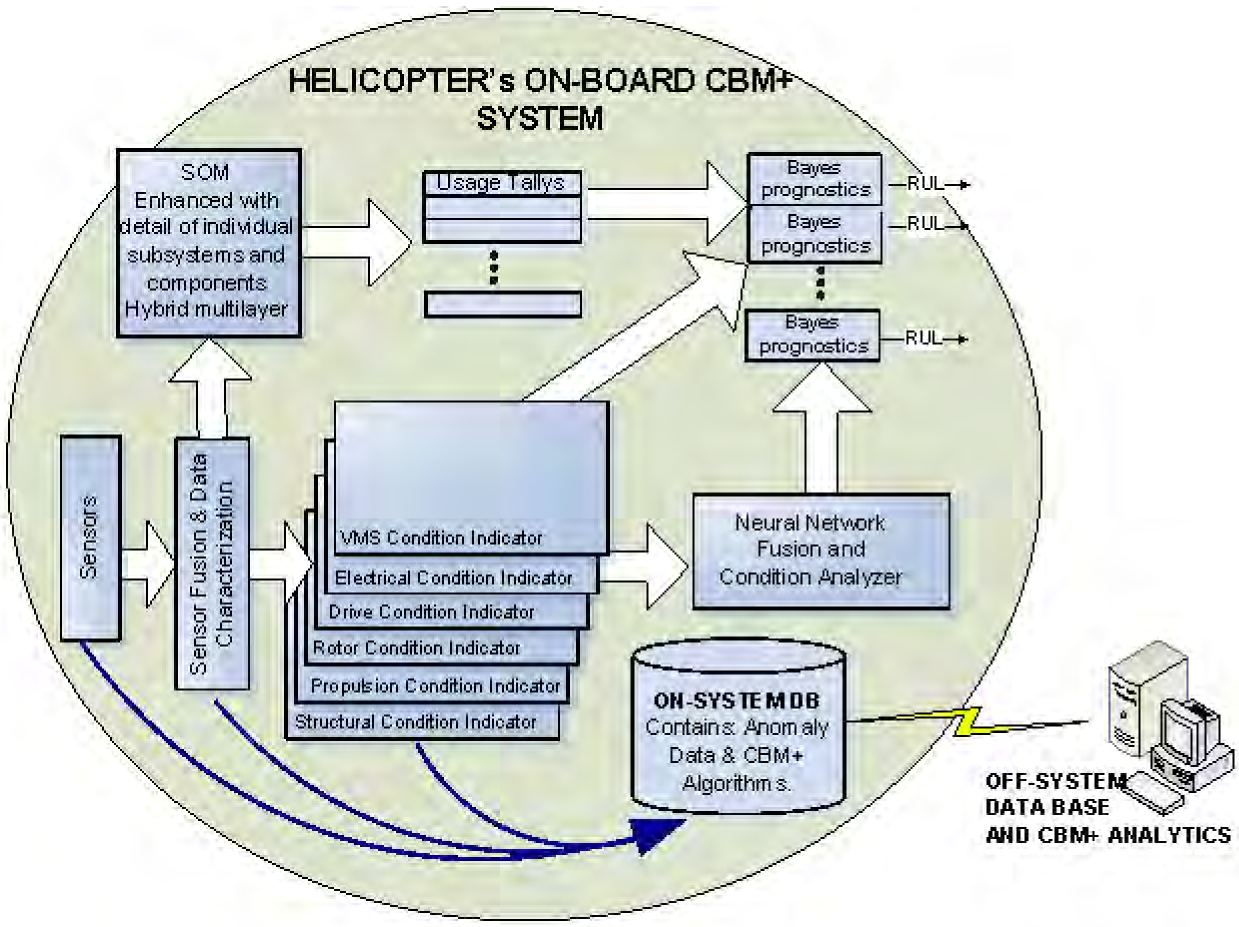

Figure 1. Architecture of the Health Monitoring System for Helicopters

and to reference usage and failure history in order to refine an estimate of the remaining useful life of the various components. It uses Bayesian decision theory to calculate the a posteriori probabilities of the need for engine maintenance based upon the current input and the current state. These predictions are more finely tuned to identify various subsystems and components of the helicopter that are likely to require service in a predetermined time frame by predicting the remaining useful life of the components.

3. ON-SYSTEM CBM+ ARCHITECTURE

The use of the 'plus' term in the CBM name adds functionality and helps define an enterprise-level CBM system architecture [1-4]. This architecture has two main components: the on-system and the off-system components, that work together to make a complete CBM+ system.

Figure 1. illustrates the overall architecture of the helicopter's on-system CBM+ processing. The on-system architecture consists of a number of dedicated modules that provide a variety of functionalities including raw data collection from sensors, data characterization, digital signal processing, extraction of condition indicators, and support of intelligent CBM+ processing.

3.1.Sensors

Sensors are mounted strategically on a helicopter to monitor the states of structural and mechanical components. They are conditioned to provide digital values corresponding to analog states of signals they are monitoring. Accelerometers are used to monitor vibration data. The sampling rate of such sensors is determined by the expected range of vibration frequencies that supply indication of faults for the monitored component. Some of the types of sensors used to monitor the health of a helicopter are as follows:

- Micro-electro-mechanical systems (MEMS) – modern accelerometers that are very small and light in size.
- Charge amplifiers (piezoelectric sensors), thermocouples, tachometers, tri-axial wireless accelerometer such as G-Link Wireless accelerometers.
- Temperature sensors installed inside bearings for monitoring conditions leading up to fault initiation
- Strain in critical components using G-Link wireless sensors.

3.2.Sensor Fusion & Data Characterization

Data Characterization is an important step in the CBM+ process. Analog and digital filters have been designed that can help attenuate the effect of high frequency noise in the measurements. Basic sanity checks and data validation methods must be used to ensure the data collected is not grossly faulty. These include checking whether the measured data and the rate at which it is changing are within predefined operational limits. Smart sensors may be used to determine whether there is any hardware problem in measurement and whether the measured data is acceptable. Also, if sensors that are not sampling data at the same frequency need to be correlated, data may have to be up-sampled or down-sampled to correlate them appropriately.

In the CBM+ system, raw sensor data is conditioned by a Sensor Fusion module. This module conditions all sensor inputs before they are further analyzed by the CBM+ system. Functionalities provided by this module are as follows:

- Noise reduction: eliminate noise from the signal using wide range of statistical signal processing algorithms. Band pass filters are also used where appropriate.
- Data validation: basic sanity check, handle missing data
- Data normalization: scale data ranges between [0..1],
- Data Correlation: Determine subsets of the sensor data that inputs to the six condition indicator blocks.

3.3. Condition Indicators (CI)

Sensor data is processed by a collection of modules that determine Condition Indicators for six subsystems in a helicopter, namely: Vehicle Management System (VMS) Control System, Electrical System, Drive System, Rotor System, Propulsion System and Structural System. Each condition indicator subsystem specializes in extracting condition indicators corresponding to the subsystem in the most effective way using the most appropriate processing algorithms. The six modules process the sensor data, extract the condition indicators and forward them to the subsequent modules for further processing. A brief overview of each of the condition indicator modules is presented here.

3.3.1. VMS Condition Indicators

The purpose of this module is to efficiently monitor a set of condition indicators for the Vehicle Management System of the helicopter. VMS components include flight control electronics, pumps, bell cranks, actuators, bearings and other components that require frequent inspections. The inclusion of VMS Condition Indicators in the CBM+ monitoring of the helicopter helps to reduce the frequency and complexity of inspections, thereby reducing the cost of labor used for inspection for maintenance.

3.3.2. Electrical Condition Indicators

This module consists of a set of condition indicators for the Electrical System of the helicopter reflecting the System's health. Wire harness health management includes detection of partially connected and/or corroded connectors, and intermittent signal conduction associated with the breaking or shorting of circuits. Understanding how the flow of electricity changes within wiring harness with partially damaged insulation or broken circuit is the key to in determining the Electrical Health Indicators [5][6].

3.3.3. Drive Condition Indicators

The purpose of this module is to provide a set of condition indicators for the Drive System of the helicopter which primarily includes the helicopter gearbox. Helicopter gearbox frequencies extend over a wide range of shaft-vibration frequencies between input and output gear mesh frequencies and cover the whole audio frequency range. It is important to separate the gear condition indicators from those of bearing in order to isolate faults accurately. Advanced synchronous signal processing techniques such as wavelet analysis, envelope analysis and time-frequency analysis are used for fault diagnosis in the gearbox [7-10] and are used to generate the Drive System's Condition Indicators.

Health and Usage Monitoring Systems (HUMS) on board helicopters collect parameters such as pressures and temperatures, bearing temperatures, wear, and, in some cases, accelerations as well. These parameters are also consolidated in the Condition Indicators generated by this module.

3.3.4. Rotor Condition Indicators

This module generates a set of condition indicators for the Rotor System of the helicopter. The Rotor Condition Indicator module provides information that indicates the state of helicopter blade health. It processes raw data collected from suitably placed sensors on rotors and their associated dynamic components and generates a vital rotor system's health condition (e.g., presence of blade damage, localize and determine severity of damage).

Maintenance of the dynamic hub components (e.g., bearings, cage, rotating components) is difficult because the components are hard to access and inspect. Extensive study of helicopter blade health has been performed on the impact damage detection on helicopter blades using sophisticated algorithms based on frequency analysis and system theory. Such methods are applied to generate the Rotor Condition Indicators [11, 12].

3.3.5. Propulsion Condition Indicators

The purpose of this module is to produce a set of condition indicators for the Propulsion System of the helicopter. This module processes raw sensor data to provide indication of the propulsion system's health conditions. Historical data on LRU (Line replaceable units) replacements and corresponding SRU (Shop replacement units) faults identified in the machine shops will also be used as input to this module. In order to reduce the variability of power predictions and increase efficiency of propulsion, this module also analyzes health and torque of the drive shaft. Technologies for crack detection in shafts (of rotating machinery) and torsional vibration analysis [13] are applied to generate propulsion condition indicators.

CBM+ monitoring of the propulsion engine is an important component of this CI module. Many methods for monitoring a rotary engine have been developed over the years, and encompass the fusion of multiple types of sensor data. These sensors include oil temperature and pressure, fuel flow rate sensors, flame detectors, and especially vibration. The vibration signal can yield a great amount of information about the health of the propulsion engine. Both time domain and frequency domain information can be monitored and used by the subsequent neural nets in the CBM+ system to create indications of engine health [14, 15].

In the time domain, various measures can be taken to provide features for analysis, included root-mean-square levels, kurtosis, and peak-to-peak levels detection. The information available in the frequency domain is generally quite richer, including once-per-rev turbine shaft vibration and higher-order resonances of it, gear mesh frequencies, combustion noise, oil swirl, and blade-pass frequencies. All of these components can be monitored for deviation from normal performance that would be indicative a deteriorating condition.

3.3.6. Structural Condition Indicators

The purpose of this module is to generate a set of condition indicators for the Structural System of the helicopter. It processes data from sensors placed on the structural frame and produces vital condition indicators based on complex algorithms [16, 17]. These condition indicators reflect the structural health of a helicopter (e.g., corrosion, fatigue, crack detection/progression, stress, temperature, etc.).

Some of the techniques used to determine Structural Condition Indicators include:

- Vibration Acoustic Modulation (VAM) technique for crack detection in a representative wing attachment fitting. VAM is a nondestructive evaluation technique that is highly sensitive to the presence of nonlinear stiffness introduced by damages and cracks.
- Impact damage detection on helicopter blades using frequency based methods.
- Thermal and impact damage detection algorithms for aircraft components.

3.4. Self Organizing Map (SOM)

The Self Organizing MAP, or SOM, technology [18] is used to discern between different operating regimes for a vehicle. It serves to interpret the higher-order sensed environment into a lower-dimension indication of the current operation for use in downstream processing.

The basic Self-Organizing Map can be thought of as a layer or sheet-like neural-network array, the cells (or nodes) of which become specifically tuned to various input signal patterns or classes of patterns in an orderly fashion. An example of a trained SOM is shown in Figure 2. The learning process is competitive and unsupervised, meaning that no teacher is needed to define the correct output (or actually the cell into which the input is mapped) for an input. In the process of training, a SOM discovers the number of classes to classify the training pattern, unlike other clustering algorithms where the number of classes must be defined.

In the CBM+ System for helicopter, the SOM discerns various flight and operating regimes, both for the overall vehicle, and for various subsystems within the vehicle. The intent is to provide guidance to the different Condition Indication algorithms in the system, assuming that there are differences in the parameters that are used in different operating regimes. For instance, a neural network that monitors shaft vibration might use a different set of weights for a highly-loaded ascent, than for idling on the ground.

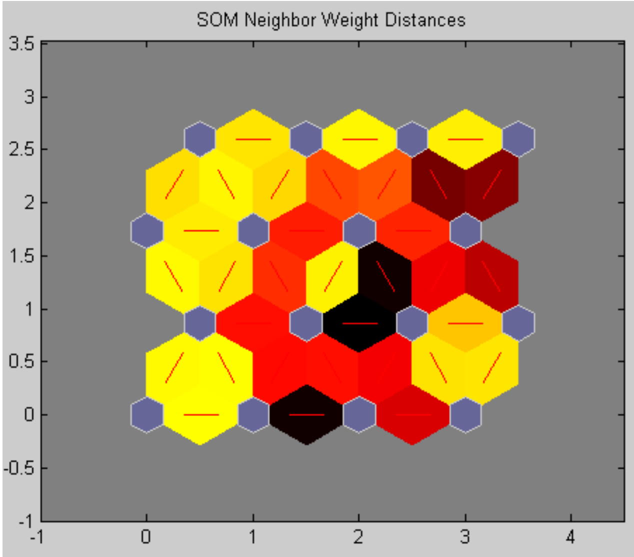

Figure 2. Self Organizing Map with 16 nodes is able to determine regimes, where the dark colors indicate the limits of each regime detected. In this figure, five regimes have been identified – the three yellow patches and two single nodes.

3.5. NN Fusion and Condition Analyzer (NNFCA)

The Condition indicators from six distinct domains of a helicopter are provided to the Neural Network Fusion and Condition Analyzer (NNFCA). The task of the NNFCA is to detect anomalous (or faulty) condition data in real time, and to distinguish between good and bad operation, supplying numerical indication of the goodness or badness detected, as seen in Figure 3.

For the NNFCA, a variation of the Fuzzy Adaptive Resonance Theory (ART) neural network model is used. The Fuzzy ART neural network, originally proposed by Carpenter and Grossberg [19] has proven to be a useful tool for pattern recognition. NNFCA uses an unsupervised learning mechanism to learn regularities in the training data by maximizing predictive generalization while minimizing predictive error in a real-time setting.

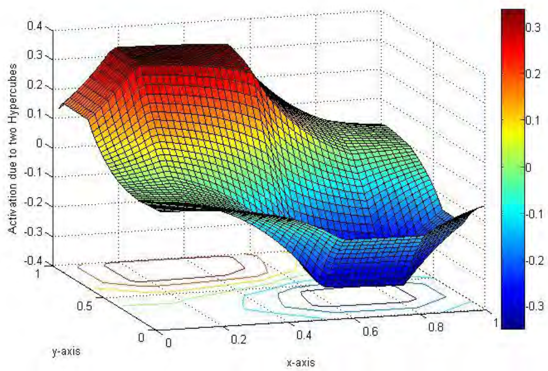

Figure 3. A graphical representation of a “good” state (red) and a “bad” state (blue) learned by NNFCA for a two dimensional input space is shown in this figure. The topology illustrates how the NNFCA classifies intermediate values.

A dedicated NNFCA is used in conjunction with each of the Condition Indicator blocks. Each NNFCA learns to correlate the Condition indicators to determine fault conditions. Each NNFCA is trained on a sequence of m-dimensional condition vectors (from the Condition Indicator boxes) as input and it learns to partitions the m-dimensional space to indicate good operating condition and faulty operating conditions. The neural network is trained on good and faulty data ahead of time. A 3-D example of the trained NNFCA neural net is shown in Figure 4. Once trained, the NNFCA is able to correlate conditions to determine the “goodness” of the operating condition. Hence, in real time the NNFCA is able to detect when the helicopter’s operating condition (for each of the 6 systems) is starting to deteriorate.

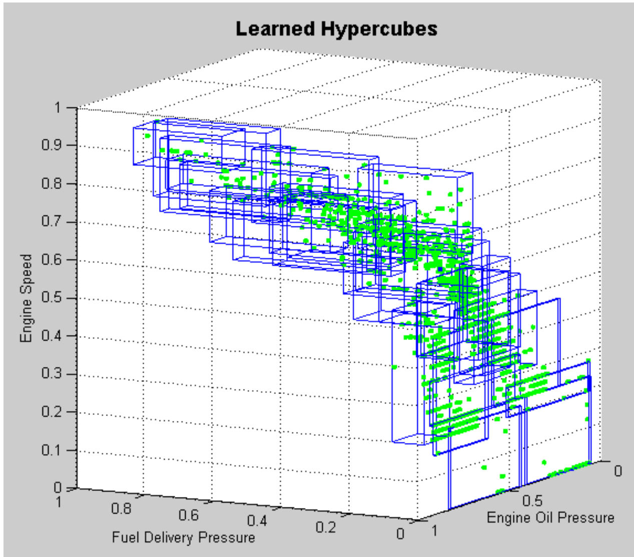

Figure 4. The operating conditions form a multi dimensional space (only three dimensions are shown here: Engine Speed, Fuel Delivery Pressure, Engine Oil Pressure) in which a vehicle operates in. In this figure, the green dots represent operating conditions that the vehicle has traversed without any faults. NNFCA learns to identify these “good” operating conditions by defining hyper-cubes in the multidimensional space. During deployment, a deviation from favorable operating condition would indicate either an error or a novelty situation. If it is the latter, the neural network is retrained to learn the novelty. The retraining would generally take place at an off-system analysis site.

An initialization procedure, prior to deploying the system for health management, includes training a neural network on favorable and unfavorable operational states of the helicopter. Once trained, it is able to detect anomalies in the helicopter’s operation and gauge its operational health. The output from NNFCA’s state analysis feedback is then provided to the Bayesian module.

3.6. Usage Tallies

The concept of usage credits is employed here to give each monitored component a certain number of credits that are expended at different rates during operation, depending on the operating regime, to provide an indication of when to perform maintenance. When the credits for a given component have decreased below a threshold, then it is time to schedule maintenance. This becomes the prime indicator of usage that is then used to predict maintenance needs. With this technique, the maintenance needs are known slight ahead of when it is dues, but not too far ahead that money is lost in needless maintenance. These are also coupled with the Bayesian prognostics to give an overall predictive mechanism.

3.7. Bayesian Prognostics

The Bayesian Prognostics section takes the a priori knowledge of mean time between failures, as well as conditional probability indications of component wear, from the usage tallies, Condition Indicators and NNFCA, and couples them into an a posteriori probability used in this section to temper the outputs of the Usage Tallies to adapt them to the currently sensed condition. The Bayesian Prognostics module provides the following:

- Reduction of inspections and preventive maintenance
- Accurate estimates of remaining useful life for components and systems
- Advanced signals of impending failure with sufficient fidelity to allow scheduling of maintenance

Based on the prognostics provided by this module, operators can make informed, risk-based decisions on the operational status of their rotorcraft.

3.8. On-System Data Store

Novel operating conditions and failure conditions not seen before will most likely generate anomaly data. All anomaly data encountered by the Sensors (and subsequent modules) in the System will be stored in an On-System Data base. Periodically, this data will be pushed on to an Off-System Data Base for further analysis. The new data will be used to re-train the Neural Network and Bayesian models.

4. Off-System CBM+

The Off-System CBM+ components, shown in Fig. 5, provide a data warehouse, a data mining and analysis capability, and a capability to update the condition monitoring algorithms and advanced prognostic health indicators that will run on the On-System hardware. The CBM+ Off-System communications could also be linked to a National-level Strategic Data warehouse [20].

Specific application tools such as Enterprise Logistics IT, prognostic algorithms, data mining and the like would comprise the Off-System Architecture layer. Data mining and Business Intelligence Tools would identify trends, improve and refine Maintenance, Diagnostic, and Prognostic capabilities.

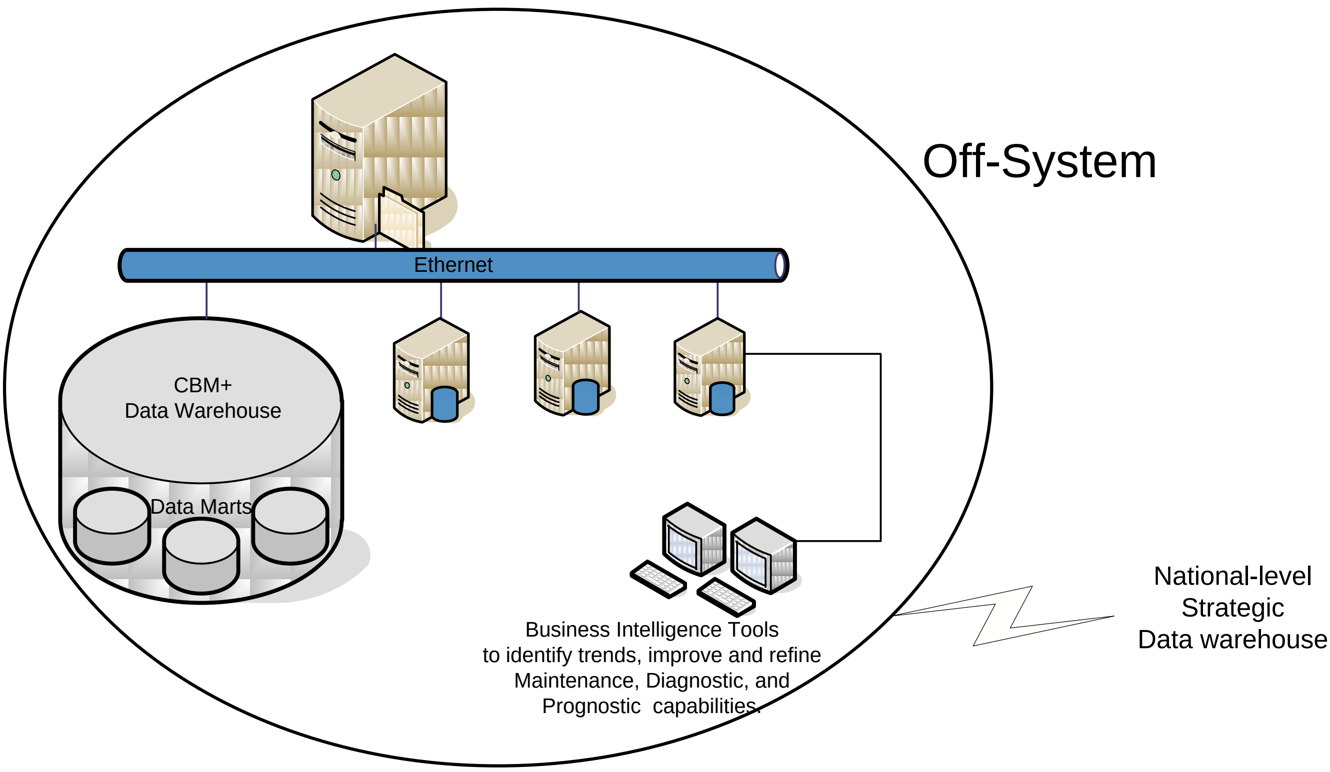

Figure 5. Off-System CBM+ Architecture.

Processing at the Off-system level is intended to provide a processing and data storage capability. Data is moved from the On-system components to the Off system environment using established data communication networks Data compression algorithms would be used to decrease the network loading required to move large data sets.

Normal operating equipment will not need to have data sent back to the Off-System location, but when anomalies are detected, or a piece of equipment is determined to be failing but the condition was not indicated, then the set of data recorded for that piece of equipment in its degraded or failing state would be sent to the Off-System site for analysis to develop an algorithm that would detect the failure in the future. This updated algorithm, perhaps consisting of neural network parameters, or other controls for the On-System hardware, would then be distributed to all On-System monitors for the affected equipment model.

The Off-System architecture requires the use of carefully designed database schemas in order to coordinate large datasets of recorded machinery operation, enabling the precise application of the analysis and condition indication algorithms.

5. CONCLUSIONS

This paper describes a Condition Based Maintenance Plus system for a helicopter that integrates a set of diagnostic, prognostic and system health assessment technologies to reduce inspection and scheduled maintenance, extend life of components between overhaul and predict failure with sufficient fidelity to allow maintenance before the system fails. The on-system architecture leverages current state of art in CBM technologies in six distinct domains in a helicopter system. The goal of this project was to create a CBM+ system to most effectively perform diagnosis and prognosis on a helicopter system, based upon the combined knowledge and research of various CBM+ efforts integrated in an open-system architecture.

Operational availability is increased, since the aircraft is not taken out of service for maintenance before service is actually needed, and also there is less of a chance of unforeseen and unplanned needs for service since the monitoring algorithms should detect the changing readiness state of the aircraft, and thus elicit a service request before failures that would otherwise not have been detectable occur. Supply chain efficiency is both enabled and required by the adoption of a CBM+ maintenance system. Efficiency is increased since only the parts that are in need of service are actually worked on. Efficiency is required, since when a part is detected to be needing maintenance, it is actually in need of maintenance, and the aircraft may likely be grounded if the service parts are not received in an appropriate amount of time.

Reference

[1] *US Army CBM+ Roadmap,* Headquarters, Department of the Army, December 13, 2007.

[2] DoDI 4151.22, *Condition Based Maintenance Plus (CBM+) for Materiel Maintenance*, DTD 2, 2007.

[3] B. Hale, An alternative vision for CBM+ for the Air Force, *Air Force Journal of Logistics,* 2005. Web page: http://findarticles.com/p/articles/mi_m0IBO/is_1_29/ai_n15674948/, viewed June 28, 2009.

[4] L.C. Jaw & W. Merrill, CBM+ Research Environment - Facilitating Technology Development, Experimentation, and maturation**.** *2008 IEEE Aerospace Conference*, Big Sky, Montana, 2008.

[5] Kautz, W.H., "Testing for Faults in wiring Networks", IEEE Transactions on Computers. V: C-23, Issue 4, pp 358-363, 1974.

[6] You Chung, C., Furse, C & Pruitt, J., "Application of phase detection frequency domain reflectometry for locating faults in an F-18 flight control harness", IEEE Transactions on Electromagnetic Compatibility, Vol 47, Issue 2, pp: 327-334, 2005.

[7] Hochmann, D. & Bechhoefer, E, "Envelop bearing analysis: theory and practice", Aerospace Conference, pp. 3658 – 3666, 2005

[8] Shu-Ting W. & Lu-Yong, Lv, "The fault diagnosis method of rolling bearing based on wavelet packet transform and zooming envelope analysis", International Conference on Pattern Recognition, V3,pp. 1257 – 1261, 2007.

[9] Deriche, M, "Bearing fault using wavelet analysis", Computers, Communication & Signal Processing Conference, pp: 197 – 201, 2005.

[10] Lebold, M., McClintic, K., Campbell, R., Byington, C. and Maynard, K.,"Review of vibration analysis methods for gearbox diagnostics and prognostics," *Proc. 53& meeting of the Society for Machinery Failure Prevention Technology,* VA Beach, VA, May 14, pp. 623-634, 2000.

[11] Schubert, L.; Kuttner, M.; Frankenstein, B.; Hentschel, D., "Structural Health Monitoring of a rotor blade during statical load test", 18th International Conference on Database and Expert Systems Applications, pp: 297-301, 2007.

[12] C. Budde, N.C. Yoder, D.E. Adams, P. Meckl, and D. Koester, "Impact Damage Detection for Fiberglass Composite Rotor Blade," in Proceedings of the Annual Forum of the American Helicopter Society, Grapevine, TX, 2009.

[13] Machorro-Lopez, J., Adams, D. E., and Gomez-Mancilla, J. C., "Crack Detection in Shafts of Rotating Machinery Using Active Sensing with an External Excitation on a Bearing", Proceedings of the ASME

Conference on Smart Materials, Adaptive Structures and Intelligent Systems, Ellicott City, MD, 2008.

[14] Richard G. Lyons, Understanding Digital Signal Processing, Massachusetts: Addison Wesley, 1997.

[15] Lybeck, N, Morton, B., Marble, S., Hess, A., & Kelly, J. “Modeling and Simulation of Vibration Signatures in Propulsion Subsystems”, IEEE Aerospace Conference, 2006.

[16] Yoder, N.C. and Adams, D.E. “A Wide-Area Crack Detection Technique for Quasi-Periodic Structural Components using Active Multi-Dimensional Vibration Sensing, 19th Advanced Aerospace materials and Processses (AeroMat) Conference and Exposition, Austin, TX, 2008.

[17] Abbas, M. Vachtsevanos, G.J. “A hierarchical framework for fault propagation analysis in complex systems”, AUTOTESTCON, 2009.

[18] Kohonen, T., “Self-Organization and Associative Memory”, New York : Springer-Verlag, 1988.

[19] Carpenter, G.A., S. Grossberg S. & Rosen, D.B., “Fuzzy ART: Fast Stable Learning and Categorization of Analog Patterns by an Adaptive Resonance System”, Neural Networks, Vol. 4, pp. 759-771, 1991.

[20] Harrison, G.A, Bodkin, M.A., Das, S., Worden, E.W., Hall, R.M, & Herzog, S.,”CBM+ System for Ship Condition Monitoring,” Proceedings of the 14th International Ship Control Systems Symposium, Ottawa, Canada. 2009.