Field Data Evaluation and Continuous Health Assessment of Critical Avionics Subsystem Degradation

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Abstract – Effectively utilizing existing on-board and at-wing data that encompasses environmental, built-in-test (BIT), vibration, and maintenance test results, can realize improved maintenance, survivability and critical failure rates via the identification of degrading components prior to critical failure. The authors have developed software to show the feasibility of onboard and at-wing prognostics using field data from an Army aircraft platform as a multi-faceted case study for predicting and diagnosing the health of a mission-critical targeting subsystem. The two use cases presented, complimentary embedded and at-wing paradigms, illustrate the mining of data from multiple sources, trending and ranking of anomalous indicators, development of a relational model for on-board BIT data, automated advanced reasoning for reduced ambiguity, and valuable avionics system prognostics. The application of these techniques to the Systems Engineering Process allow for the ground truth feedback of valuable engineering test results for validation of the Prognostic Health Management (PHM) process.

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1. INTRODUCTION

Viewing aircraft components from a systems perspective allows for the development of interconnected relationships that can be exploited and provide substantial gains to the overall effectiveness of present maintenance practices. Additionally, noninvasive monitoring of system condition indicators enable early detection, tracking, and trending of impending faults leading to improved diagnostics and reduced cases of critical failures. The demonstrated technology permits the observation of fault indicative behavior and scheduling of component downtime prior to critical failure, thus providing increased mission readiness and cost saving benefits derived from Predictive Health Management (PHM).

The authors' study focused on the demonstration of an automated prognostic capability for a mission critical electronic system onboard an Army aircraft, the targeting system. The case study encompasses two complimentary implementations: an embedded prognostics case and an at-wing prognostics case. The targeting system provided added benefit as the test case since it offered a good representation of other aircraft subsystems in that it was:

(1) Mission critical

(2) Heavily interconnected among avionic units

(3) Able to provide BIT / continuous data

(4) Susceptible to ambiguous diagnostic test results

The entire case study manifests itself in two demonstrated capabilities. The first technology case derives a leading set of condition indicators from the available data as metrics for monitoring the health of the targeting system and for detection of anomalous behavior. The second case utilizes a larger available data set at-wing to assess component health and provide prognostic information yielded from data fusion and intelligent reasoning algorithms. Reduced ambiguity in determining the component at fault in an avionics framework results and provides superior gains over current practices, which fail to account effectively for system interdependencies and previous anomalies. In both cases, multiple knowledge discovery techniques reduce the solution space to manageable size, advanced reasoning technologies provide truer condition indicators, and knowledge fusion offers the capability of providing a high confidence prognostic output.

At the onboard or embedded level, the authors used SignalPro™ to identify, track, and characterize continuous component condition indicators. The SignalPro™ software validates and diagnoses signal health by employing a combination of signal processing, statistics, and data-driven modeling techniques. A model of the targeting system derived from healthy data sets formed a baseline for detecting faulty data and enabled the identification of anomalous behavior in the minutes prior to a critical targeting system fail BIT.

The at-wing study demonstrated the capability of ambiguity reduction among ranked subsystem components using intelligent reasoning algorithms and systems-level knowledge based on a connectivity matrix. The connectivity matrix modeled the targeting system from a system's level perspective by incorporating relationships among interconnected components via BIT sets and enables added diagnostic value over the initial design intent of the BITs. Many of these BIT indicators are reset or discarded during normal operation. However, these messages, when viewed from this inter-connected system point of view, gain value over the original BIT design intent.

A positive-negative evidence reasoning system incorporates real fault probabilities and false alarm rates in this model to infer a likelihood of failure. The result is an ambiguity group ranking for each component that changes as new evidence becomes available. The cases presented provide a framework for streamlined prognostics from the capture and tracking of data onboard through to component diagnosis at the depot level, and show the feasibility of generating a health assessment, dynamic with time, of the components identified. The ability to integrate health information at the embedded level with at-wing data offers a powerful capability for identifying anomalous line replaceable units (LRUs) prior to depot level testing, reduces turn around time, and decreases the overall instances of cannot duplicate (CND) and cannot verify (CNV) test stand results. A full demonstration of the software and its benefit for current and future avionics systems will be provided with the paper's presentation**.**

2. DATA SOURCES

Multiple information sources provided a large set of data useful for developing a practical prognostic framework. These sources included:

(1) Bus Monitor Data

(2) Electronic Logbook (ELOG) Data

(3) Electronic Maintenance Action Data

(4) Interactive Electronic Technical Manual (IETM) Data

(5) Off-System Diagnostic Test Results

Bus monitor data provided monitored fault / exceedance parameters, initiated, power-up, and continuous BIT, and continuously sampled features. Electronic maintenance action data offered vibration-monitoring recordings, time series parameters, and BIT data. ELOG records provided the ability to correlate maintenance actions with critical fault instances and IETM data presented applicable technical engineering knowledge and diagnostic protocol information. The Off-System Diagnostic Test Results provide the ground truth validation of performance characteristics for the degraded component. The large amount of symbolic, numeric, and textual data swamps the analysis process and generates a large solution space. The approach taken accommodated the varied data, minimized and optimized the solution space, and provided the relationships and evidence that aided in the development of a model for the application of Predictive Health Management (PHM) techniques.

Multiple knowledge discovery and data mining techniques permitted the extraction of feature parameters from the available data. Analysis using SignalPro™ identified subtle condition indicators that precede system failure. The development of a partial system model derived from available evidence incorporated the interrelationships amongst hundreds of parameters obtained from healthy data provided during an initial training period. The software measures parameter readings and compares them to model predictions to assist in determining fault conditions, and provides signal estimates in the event of degraded or missing values. Figure 1 presents the high-level training and modeling process flow.

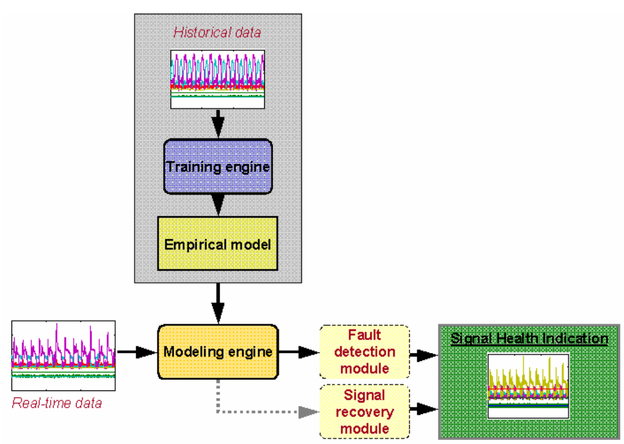

Figure 1 – SignalPro™ Training and Modeling Process

SignalPro™ identified key parameters and modeled targeting system performance to provide early detection of impending component failure. The data operated on manifest itself in over 600 parameters presented in database format.

3. EVIDENCE DISCRIMINATION

Identifying Critical Parameters for Embedded Diagnostics

Sensitive condition indicators can reside in seemingly normal operating data, subtly indicating that problems lie ahead. Correlation of known component failures, using BITs, with available continuous parameters allow for effective diagnostics and early warning features that lead to real-time prognostics. The applied correlation process distilled system information by retaining only signals pertinent to the failure of interest and created a sensitive, compact model for failure diagnostics. In the case presented, the critical failure related to the aircraft's targeting system was indicated by a Targeting System Fail BIT. The calculated correlation coefficient magnitude of all available parameters resulted in a reduced set of correlated parameters related to the Targeting System Fail BIT and degradation of the Targeting System subsystem. Figure 2 shows the parameters most highly correlated to the Targeting System Fail BIT.

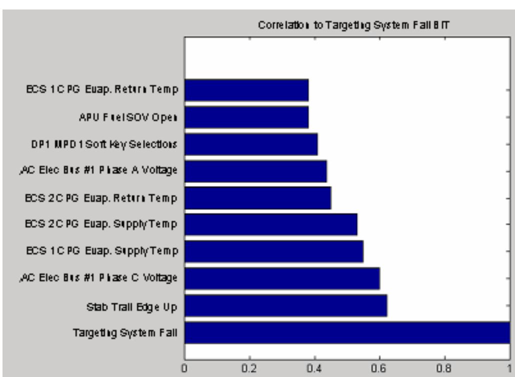

Figure 2 – Derived Correlated Parameter Set

After condition indicators were identified, they were tracked and trended as indicators of anomalous behavior. The plot in Figure 3 illustrates the model fidelity achieved by using preprocessing correlation and subsequent parameter modeling. The example displays the results for the ECS 1 CPG Evaporative Supply Temperature parameter. The top panel displays the measured value (red) and the SignalPro™-estimated value (green). The center panel shows the residual, or difference, between these two values and the +/-3 standard deviation limits for acceptable residual as determined during the training session. The bottom panel shows the transient accumulation of residual and its acceptable limits.

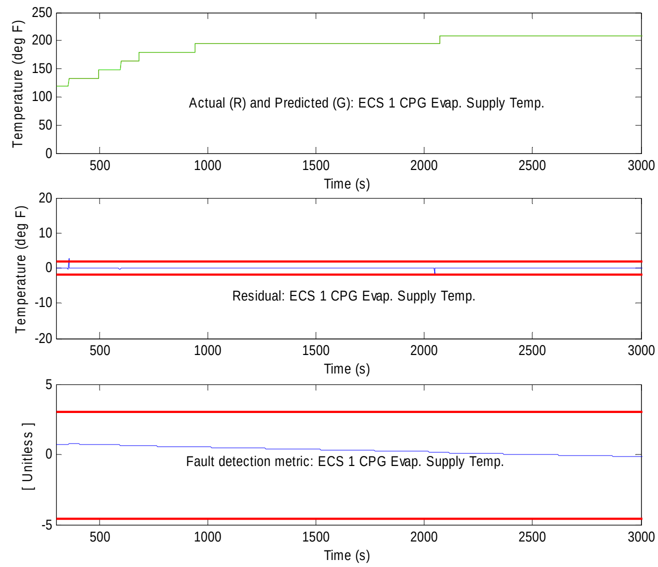

Figure 3 – Measured and Modeled Signal, Residual, Detection Metric (ECS 2 RH EFAB Evaporative Return Temperature)

Similar plots were generated for the other system features to assess the model of the targeting system. As noted in Figure 3 by the near zero residual, the model successfully validates the data with high accuracy and clearly indicates that when initially trained on healthy data the data-driven modeling approach can accurately model the targeting system.

Accurate system modeling leads to the potential for incipient fault detection via the tracking and trending of feature values and to the generation of indicators of anomalous behavior. Figure 4 illustrates the outlined capability with an example of an Evaporative Cooling Temperature parameter.

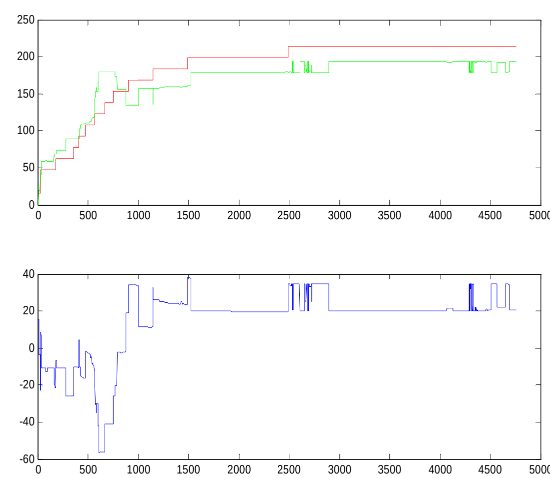

Figure 4 – Evaporative Cooling Temperature (Meas., Red; Est., Green; Residual, Blue)

The top panel shows the measured Evaporative Cooling Temperature (red) along with the model-estimated value (green). The middle panel shows the residual between these two values. The cooling temperature is consistently higher than expected after an initial ramp-up period, suggesting a potential problem. The model estimates the cooling temperature as a function of ambient conditions (outside air temperature and atmospheric pressure), therefore the disparity between the actual and predicted values due to a change in conditions is highly unlikely. A divergence anomaly is more probable and has to be considered a warning of degrading conditions or impending failure.

Identifying Condition Indicators for At-Wing Diagnostics

A preliminary discovery step performed on the available data offered a reduced set of high value condition indicators correlated to targeting system failure. Application of a system-level perspective permits the construction of a connectivity matrix that illustrates the relationship between failure evidence and subsystem components. Exploitation of the identified relationships provides insight into the origination of anomalies.

The simplified connectivity matrix, Figure 5, demonstrates the interconnectivity and dependency of various subsystems by way of representative BIT sets. The system under investigation, the targeting system, does not exist on its own, but also functions with dependencies on the pilot head mounted display (PHMD), copilot/gunner head mounted display (CHMD), environmental control system (ECS), and the MIL-STD-1553 bus. A system-level perspective of the avionics system allows for the generation of a connectivity matrix based on subsystem knowledge and the BIT set relationship between them. The approach offers the first step to diagnostic ambiguity reduction among various subsystems.

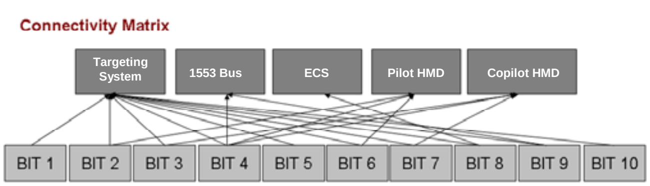

Figure 5 – Simplified Connectivity Matrix

Analysis of the connectivity matrix depicts a relationship between the targeting system and the PHMD via BIT 6, the CHMD via BIT 7, and the 1553 bus via BIT 4. An understanding of the interconnected system dependencies allows for identification of those subsystems related to the subsystem of failure, in this case, the targeting system.
Furthermore, the defined interconnectivities provide a system level knowledge for integration into an intelligent reasoner capable of ambiguity reduction and faulty component ranking.

4. EMBEDDED USE CASE

Identification of parameters highly correlated to the targeting System Fail BIT offer metrics for tracking and trending within a subsystem. In the embedded case study presented, the failure is known *a priori*, and the applied data analysis and signal processing techniques provide a Proof of Principle (PoP) for embedded monitoring and diagnostics with a faculty for low-level reasoning.

The authors' have designed a user interface in MATLAB to demonstrate the attributes of an avionics PHM system. The embedded interface offers a visual of the key features of interest and the ability to track their values over time. The features tracked are those high-value parameters identified earlier and correlated to a critical targeting system failure indicated by the Targeting System Fail BIT returning a 'true' value. Figure 6 illustrates a screenshot of the embedded portion of the PHM graphical user interface.

The PHM tool's provisions include the ability to visually track and trend the magnitudes of feature parameters over time. The continuous values of interest are tracked and compared to their expected value trends derived from available healthy data sets. Parameter values falling outside statistically determined threshold levels point towards anomalous behavior. As time progresses, both discrete and continuous parameters can be monitored as sources of anomalous behavior within the subsystem. The interface demonstrates the ability to accumulate evidence derived from anomalous behavior and factor this evidence into forming an assessment of subsystem health with increasing confidence as time progresses. The interface also shows the capacity for early fault recognition and usage of recorded faults in providing dynamic system health assessments.

In the embedded case, multiple evidence elements provide an indication of targeting system failure. The rise in evaporative supply temperatures queues the onset of deviant behavior. Minutes later a recorded Targeting System Fail BIT returning 'true' indicates a potential problem identified by the targeting subsystem. Finally, the Targeting System Electronic Unit Fail BIT returns 'true' as the evaporative supply temperature peaks and the targeting system is deemed to be in a critical state.

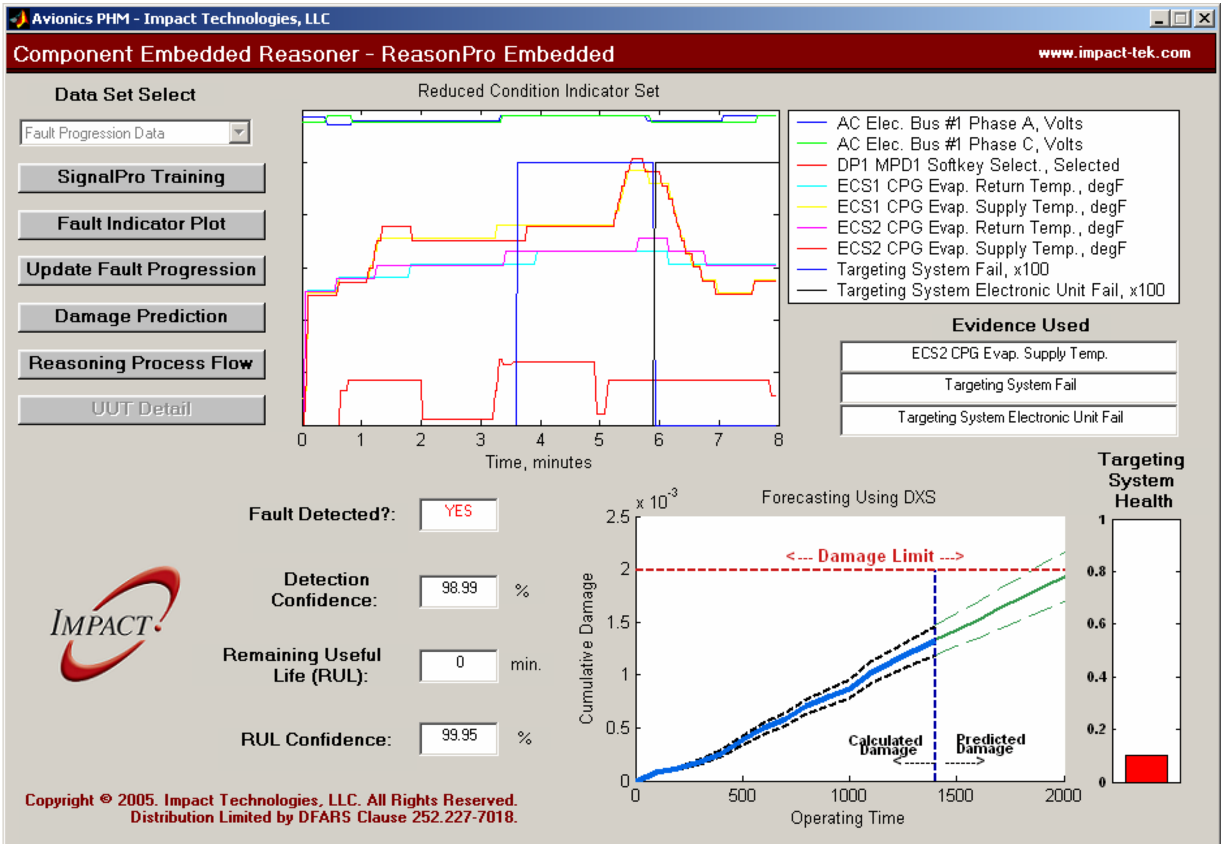

Figure 6 – Embedded Avionics PHM Case Study User Interface

5. AT WING USE CASE

The connectivity matrix of Figure 5 provides the foundation for understanding the interdependence of the avionics subsystems related to the targeting system. Data mining efforts resulted in an instance of targeting system failure. The at-wing use case study offers a graphical user interface to monitor the ranking of multiple subsystems and provide reasoner-enabled ambiguity reduction to allow accurate diagnosis of subsystem failure.

Current at-wing test methods result in an ambiguity group of culprit subsystems when a maintenance action is flagged. Often, multiple line replaceable units (LRU) are pulled for further testing at the depot level because an accurate at-wing diagnosis cannot be made. The capture of multiple evidence sources, including known system dependencies provided by a connectivity matrix and associated BITs, provide a means for intelligent reasoners to afford ambiguity reduction at-wing. Figure 7 illustrates the user interface implementing such a reasoner and decision support tool.

The user interface below demonstrates the ranking of subsystems within the ambiguity group. The ambiguity group includes the PHMD, CHMD, ECS, 1553 bus, and the targeting system. Data mining efforts offer BIT data related to the elements of the ambiguity group. The authors' employ a positive/negative evidence-based reasoner as a means of ranking the ambiguity group. As Figure 7 demonstrates, the ambiguity amongst elements begins high. As time progresses and more BIT evidence is collected and utilized in the reasoning operation the degrading targeting system rises to and stays atop the ambiguity group with increasing confidence.

From an at-wing perspective, available evidence has been used more effectively than current methods provide and results in accurate diagnosis of the subsystem at fault and an indication of its impending failure one to three days prior to actual critical failure.

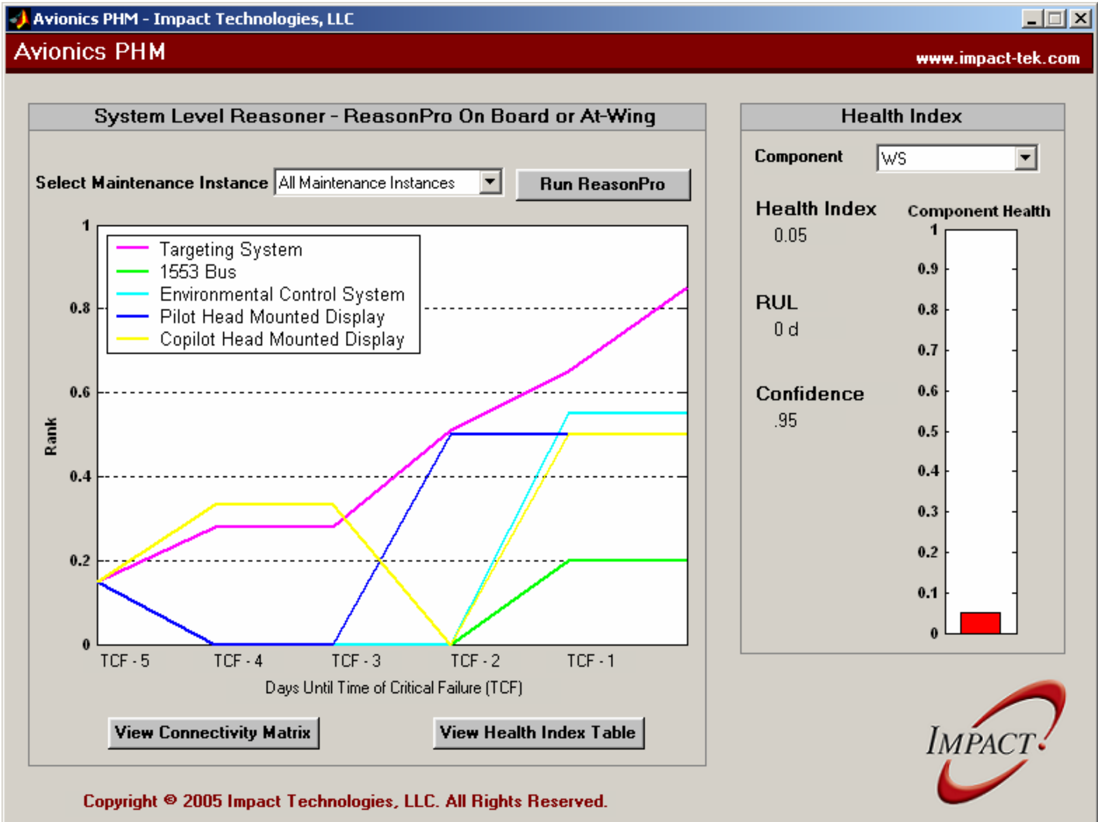

Figure 7 – At-Wing Avionics PHM Case Study User Interface

6. INTEGRATED PHM METHODS

Implementation of both embedded and at-wing PHM systems provide significant advantages over the application of only the embedded or the at-wing case. Usage of both types offers an inherent benefit for the overall avionics architecture and adds value to each of the constituent PHM systems, the embedded and the at-wing. The major benefits that dual implementation provides include:

(1) Advanced insight into subsystem failure modes

(2) Additional evidence sources for intelligent reasoning

(3) Component-level and system-level health prognosis

(4) Architecture supporting information continuity

The embedded PHM scheme described yields benefits beyond mere identification of anomalous behavior at the subsystem component level. Information, recorded and retained, offers valuable evidence for at-wing reasoner-enabled diagnostics and prognostics. The known anomalous indicators logged by an embedded PHM system provide high-value evidence that when integrated with BIT results from at-wing PHM processes enable a truer interpretation of failure conditions and allows for higher confidence diagnostic outputs.

The integration of embedded PHM provides the additional capability of providing insight into a LRU's failure mode even prior to testing at the depot level. The at-wing diagnosis offers ambiguity reduction and decision support for which LRU to pull, while results from the embedded level yield advanced insight into potential failure modes derived from identified anomalous behavior that can be addressed at the depot level.

The at-wing PHM scheme naturally gravitates towards system level diagnostics and prognostics, while an embedded scheme offers diagnostics at a component level. The advantage of a PHM architecture that leverages these two perspectives permits information continuity from the on-board to depot level thus retaining failure mode, maintenance, and environmental data for the unit under test (UUT).

7. VALIDATION & VERIFICATION

Condition-based maintenance (CBM) technology strives to identify incipient faults before they become critical. Although CBM holds many benefits compared to other maintenance types it is not yet commonly utilized in industry or military applications. A reason for this might be that the maturity level in complex technical CBM systems is too low. The fear of investing a lot of money without knowing exactly what will come out of it might be yet another. An approach that utilized an off-system diagnostics platform to validate and verify the electronic prognostics system was used to reduce these risks. The diagnostics system utilizes a model-based approach to detect deviations and if a deviation is detected the model is used to identify the problem. The mining of this data provides "ground truth" feedback into our on-system and at-wing prognostics application. In effect, the off-system diagnostics platform becomes an adaptable V&V Test Bench capable of identifying false alarms, running electronics to failure to calculate remaining life, provides a method to classify fault types, and supports methodologies for affordable tests.

8. CONCLUSIONS

The authors have presented two related case studies that demonstrate the feasibility and complimentary benefits of implementing embedded and at-wing predictive health management infrastructures for an avionics platform. The subsystem investigated was the targeting system and available data offered two case studies for monitoring and assessing component health degradation. The team presented the potential for anomaly detection indicative of faulty behavior at the component level and the usage of BIT information at-wing to reduce ambiguity using an intelligent reasoner to provide confidence-based decision support for subsystem maintenance. Applied signal processing and data mining techniques were presented that reduced the solution space to manageable size compared to the extensive set of varied available data. Additionally, the modeling methods employed generated a reliable system model for monitoring and identifying fault indicative parameters and detecting degrading components prior to critical failure. The software modules developed offered valuable graphical user interfaces for monitoring, tracking, and trending of continuous parameters in the embedded case, and afforded rank progression, subsystem health assessment, and health-based decision support in the at-wing case. Finally, the innate benefits of an integrated PHM system with implications for enabled data continuity from the onboard to depot maintenance levels were discussed.

9. ACKNOWLEDGMENTS

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10. BIOGRAPHY

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