IEEE Standards for Prognostics and Health Management

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Abstract *– Recently, operators of complex systems such as aircraft, power plants, and networks, have been emphasizing the need for online health monitoring for purposes of maximizing operational availability and safety. The discipline of prognostics and health management (PHM) is being formalized to address the information management and prediction requirements for addressing these needs. In this paper, we will explore how standards currently under development within the IEEE can be used to support PHM applications. Particular emphasis will be placed on the role of PHM and PHM-related standards with Department of Defense (DOD) automatic test systems-related research.*

Keywords *– Prognostics, PHM, CBM, AI-ESTATE, SIMICA*

I. INTRODUCTION

In 1976, the IEEE established the Standards Coordinating Committee 20 (SCC20) for purposes of standardizing on the Abbreviated Test Language for All Systems (ATLAS). Since then, SCC20 has expanded its scope to develop standards for larger system-level test and diagnostic related systems. In 1989, the IEEE approved a project authorization request (PAR) for SCC20 to develop a new standard focusing on diagnostic systems that use techniques from the maturing field of artificial intelligence—the Artificial Intelligence Exchange and Service Tie to All Test Environments (AI-ESTATE) standard under project P1232. In 1995, SCC20 approved and published the AI-ESTATE standard, IEEE Std 1232-1995, and in 2002, the standard was updated. Today, SCC20, under the management of its Diagnostic and Maintenance Control (DMC) subcommittee is completing a new update to the AI-ESTATE standard, and this standard is emphasizing its broad scope by embracing PHM-related issues.

The DOD ATS Framework Working Group is a multi-service/industry/academic partnership that is focusing on defining an information framework and identifying standards for next-generation automatic test systems (ATS). Based on work in the 1990s when the ATS Research and Development Integrated Product Team defined a set of “critical interfaces” for ATS, the current working group has been selecting, supporting the development of, and demonstrating commercial standards to be used in ATS. In 2007, the working group decided to expand its scope to embrace information requirements for PHM as well and added two new “elements” to its framework—an element for prognostic data (PROD) and an element for prognostic services (PROS). The working group decided to focus on these elements to parallel the diagnostic data and diagnostic service elements already contained in the framework.

PHM has been defined as “a maintenance and asset management approach utilizing signals, measurements, models, and algorithms to detect, assess, and track degraded health, and to predict failure progression [1].” As defined, PHM encompasses much more than is currently addressed by SCC20; however, the AI-ESTATE standard has been found to address many PHM issues related to fault/failure diagnosis. The DMC is currently developing standards under the Software Interface for Maintenance Information Collection and Analysis (SIMICA) project (P1636) that are likely to address additional information management requirements for PHM. These standards capture historic information that can be used to analyze maintenance and diagnostic processes and to tie these analyses to system fleets or to individual systems. The result is a collection of standards that can support diagnostic maturation and PHM process improvement. The focus of this paper is on applying the AI-ESTATE and SIMICA standards in PHM systems. The discussion in this paper highlights the recent results in developing these standards and focuses on how they can be used to satisfy PHM information management requirements.

II. APPROACHES TO PHM

Generally, PHM systems incorporate functions of condition monitoring, state assessment, fault or failure diagnostics, failure progression analysis, predictive diagnostics (i.e., prognostics), and maintenance or operational decision support. Ultimately, the purpose of a PHM system is to maximize the operational availability and safety of the target system.

The primary area of interest in this paper is the impact and potential benefit of standardization supporting interoperability for PHM systems. More specifically, the area of interest lies in the “predictive” portion of PHM—the ability to predict from information about some system state when a significant future event affecting the performance of the system (such as failure) might occur. Often, this prediction is characterized as estimating the remaining useful life (RUL) of a component or system [2], [3]. Standardization in information systems involves careful, formal definition of concepts and information elements for the target system. We believe RUL is misleading at the system level in that it suggests no repair is possible, thus extending the RUL of the system. Therefore, we suggest the term time to fail (TTF) but

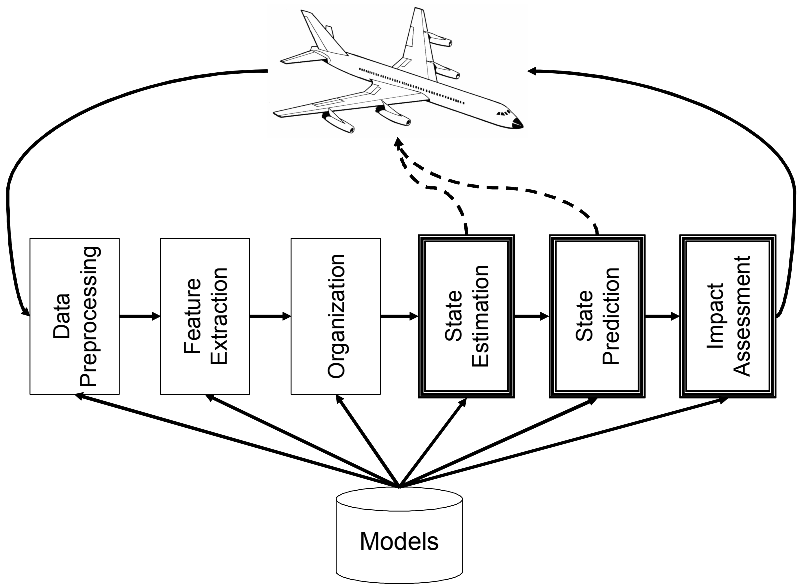

Figure 1. Notional CBM/PHM System

note possible confusion with the TTF measure as defined in [4]. Specifically, Vachtsevanos *et al.* define TTF as "the duration between initiation of the fault and the time when the failure occurs." As an alternative, we define TTF to be "the time from a measurement of system state to some failure of interest in the system."

One can think of PHM as being applied in an operating environment in which there is interaction with and feedback to the system being monitored (Figure 1). When building a PHM system, three components are necessary for prognostics to be effective (which are highlighted in Figure 1)—the ability to estimate the current state of the system, the ability to predict future state, and thereby time to fail, and the ability to determine the impact of the assessment on system performance and the need for corrective or mitigating action. In all three cases, system-specific models must also be provided. In support of these components, several approaches are being applied.

Physics Model-Based Methods: Perhaps the most effective method in terms of high-fidelity prediction of system degradation is the application of physics-of-failure (POF) models to structural degradation and structural health monitoring systems [5]. POF methods focus on issues such as material deformation, fracture, fatigue, and material loss. Recent attempts at applying POF methods to electronic prognosis have focused on the material degradation of interconnects and substrates [6], [7]. While highly accurate, POF approaches tend to be computationally prohibitive to apply at the system level. This limitation has led to alternative approaches being developed and applied, sometimes in combination with POF methods.

Reliability-Based Methods: Perhaps the simplest approach to predicting failure is based on statistical reliability models of component failure. Recall that reliability is defined as the probability that a component or unit will be functioning at time t [8]. Usually, reliability predictions are used to estimate future failure based on current test results by applying a probability distribution such as the exponential distribution (i.e., $P(D_i) = 1 - \exp[-\lambda_i t]$). One of the principal shortcomings of using the exponential distribution is that it imposes a "Markov" assumption, meaning that the future prediction of a failure is independent of the history of the unit given the current measurement. Given the strength of this assumption, alternative reliability methods have applied the Weibull distribution for the predictions since it relaxes the assumption of constant failure rates as well as the Markov assumption [9].

Data-Driven Methods: In a sense, POF and reliability-based methods form end-posts along a spectrum of techniques for prognostic methods. POF methods depend on high-resolution models but do not scale well. Reliability methods rely on statistical characteristics of populations of systems and do not handle idiosyncrasies of specific systems. As an attempt to provide a compromise approach, data-driven methods such as regression models [10], time series analysis [11], and neural networks [12] are being applied. Each offer an advantage of being able to learn models based on empirical data but also suffer from the inability to learn portions of the model where no such data exists.

Probability-Based Methods: Lessons drawn from signal processing, target tracking, and state estimation have identified a number of probabilistic models showing promise for PHM. Specifically dynamic Bayesian network (DBN) architectures such as hidden Markov models (HMM) [13] and Kalman filters [11] have been suggested as methods for using historical, sequential data to predict future failure. The concern with these models relates to the so-called "diffusion of context" phenomenon where, because of conditional independence, the affect of past experience diffuses the ability to predict. This, in fact, is directly related to the Markov assumption also inherent in the reliability models discussed above [14]. The use of so-called "input-output hidden Markov models" has been suggested as an approach to combat this problem [15].

As should be evident from the above review, the "silver bullet" for PHM systems has yet to be discovered or developed. In fact, arguably, PHM technology is still very much in its infancy. Therefore, it is interesting to be considering standardization of PHM elements. Even so, the Machinery Information Management Open Systems Alliance (MIMOSA) has adopted the development and support of the Open System Architecture Condition Based Management (OSA-CBM) standard that purports to provide a standard architecture for CBM and PHM systems.

OSA-CBM is an architecture standard organized around seven "hierarchical" layers: sensor/transducer, data acquisition, data manipulation, state detection, health assessment, *prognostic assessment*, and advisory generation. Of particular interest here are the health assessment, prognostic, and decision support layers [16]. Using the three key components of a PHM system identified above, we see the health assessment layer being responsible for health state estimation, and the prognostics layer being responsible for predicting time to fail. Both layers must address uncertainty management and confidence prediction. These layers are shown to be connected with state detection below and advisory generation above.

Currently, the OSA-CBM standard provides a Unified Modeling Language (UML) model identifying key "objects" to be defined in a standard CBM system [17]. Unfortunately, current implementations of the OSA-CBM architecture have not incorporated the means of standardizing the semantics of the information being communicated between system components, This is where the work of SCC20 hopes to contribute and is what we discuss next.

III. STANDARDS IN MAINTENANCE AND DIAGNOSTICS

Fundamentally, prognosis is an extension of fault or failure diagnosis. In addition, given the fact prognosis attempts to anticipate and predict impending failure, the nature of the maintenance process under a PHM system is fundamentally different from a maintenance process based on taking corrective action in response to a reported failure. Currently, few standards exist of direct relevance to prognostic systems and PHM systems; however, because of the close ties between PHM and traditional diagnostic and maintenance systems, several standards for the maintenance and diagnostic communities can be applied to PHM. As we will discuss below, it is also hoped that these same standards will serve as a starting point for the development or maturation of standards for PHM.

Since the mid 1970s, SCC20 has been developing standards, originally focused on test specification and test programming, but more recently focusing on test, diagnostics, and maintenance system interfaces. These standards, developed under the auspices of the IEEE Standards Coordinating Committee 20 on Test and Diagnosis for Electronic Systems include the Signal and Test Definition standard [18], the Automatic Test Markup Language (ATML) family of standards [19], the AI-ESTATE standard [20], and the SIMICA standards [21]. Of particular interest to us are the AI-ESTATE and SIMICA standards. Within the SIMICA family are two additional standards—Test Results [22] and Maintenance Action Information [23].

A. AI-ESTATE

IEEE Std 1232 describes the information comprising the diagnostics domain, i.e., information related to system test and diagnosis. The description of the diagnostic domain enables the exchange of diagnostic information between applications. IEEE Std 1232 also supports modular diagnostic architectures and interoperability with other test-related software assets. The 1232 standard was developed using information modeling practices with the ISO EXPRESS modeling language [24], resulting in the definition of five models addressing static and dynamic aspects of the diagnostic domain.

Based on the formal information models, AI-ESTATE provides two different mechanisms for exchanging diagnostic information. The historical approach uses the Standards for the Exchange of Product model data (STEP) Physical File Format defined in [25]. This format specifies a simple ASCII, flat file utilizing tokens within an attribute-value structure and must be used in conjunction with the EXPRESS Schema. SCC20 also plans to use an XML schema consistent with the information model based on ISO 10303 Part 28 [26].

Finally, in addition to the information models being developed, AI-ESTATE defines a set of software services to be used when integrating a diagnostic reasoner into a test system. The reasoner services are being specified using the Web Services Description Language (WSDL) [27], arising mostly due to the increased emphasis on web services and XML for exchanging information.

Given both the published AI-ESTATE and the current revision being developed by SCC20, several relationships are apparent between AI-ESTATE information elements and key components of PHM systems. For instance, it is sometimes desirable to qualify test using measures of confidence, and failure/fault predictions can be provided with associated probabilities and levels of confidence. That said, AI-ESTATE is currently limited to assigning discrete outcomes, both to tests and diagnostic conclusions. Currently, AI-ESTATE is also limited to supporting systems that provide state assessments at the current point in time, assuming propositional representations of the associated diagnoses. This is significant because, currently, none of the models support time to fail predictions. Prior proposals have been supplied to SCC20 for supporting temporal logic [28] and dynamic Bayesian networks that would be useful for prognostic algorithms [29]; however, neither was considered sufficiently mature to be included in the standard. In fact, it is unclear that industry consensus exists on the semantics of an elementary TTF metric at this point in time.

B. *Test Results*

The current draft of the SIMICA standard is focused on providing a top-level information model for maintenance information. This model will provide an "umbrella" representation to correlate the semantics of several lower-level partitions of the system operational and maintenance information domain. While that information model was being completed, two of those lower level "component" standards within the SIMICA family have been under development as well. The first—SIMICA Test Results—has been approved and published as a trial use standard.

The Test Results standard provides an XML schema and accompanying information model to specify a means for exchanging test measurement information. The focus of the standard is to capture historical information about the actual conduct of tests and includes information such as UUT identification, measurements, specified test limits, and information specific to test session such as setup, test sequence, and fault indictment information [22], [30].

Typically, PHM requires systems that perform online monitoring of the system of interest. The 1636.1 standard provides direct support for a PHM system in that it captures the history of the monitored data. Measurements, test limits, outcomes, and calibration information, coupled with time stamps for when the data was collected, enable offline processing of the data to determine system state, perform diagnosis, and when coupled with a prognostic model, contribute to the prediction of future system state.

Since the 1636.1 standard emphasizes data exchange through XML, real-time applications of the standard are not directly supported. A PHM system can, however, make use of the information model to determine the relevant types of information to be captured and the definitions, relationships, and constraints on that information necessary to ensure interoperability between other components that may require the data (such as a diagnostic system). By applying a similar "service-oriented" architecture for the PHM system as that proposed in AI-ESTATE, online processing of the test results could be supported in a standardized way.

C. *Maintenance Action Information*

Recently, a new initiative was undertaken that was initially intended to support the capture and processing of historical maintenance data for military systems. This process involved surveying maintenance processes for each of the US military services to identify common, essential maintenance information that is captured on maintenance action forms (MAF). SCC20 then proceeded to generalize the information, to address maintenance processes in non-military applications. The result was the development of an information model and XML schema for maintenance action information (MAI), being standardized under IEEE P1636.2 [23].

The MAI standard is not intended to support a PHM process directly, as the Test Results standard or AI-ESTATE might. Instead, MAI captures what has been done with respect to a system of interest, either in response to a failure or during preventative maintenance. Nevertheless, the information captured in an MAI document can be used to perform data mining and data analysis to support diagnostic and maintenance system maturation as well as to assist in developing prognostic models and systems.

D. *Related Non-IEEE Standards*

This paper has focused on the IEEE standards that have potential in supporting PHM. Currently, no IEEE standards exist that are dedicated to PHM; however, standards exist outside of the IEEE, in addition to OSA-CBM, that focus on issues such as health monitoring and condition-based maintenance (CBM).

ISO 10303 Part 239 defines an "application protocol" for product life cycle support (PLCS) [32]. The purpose of this standard is to facilitate exchange of information about complex "engineering assets" for the purposes of life cycle support. The data exchange is accomplished through the definition of data exchange specifications (DEX) tied to specific domains and derived from the PLCS information model.

With recent emphasis being placed on modifying product maintenance practices from reactive to condition-based or "just-in-time," product-specific data has become critical. The Organization for the Advancement of Structured Information Standards (OASIS) has developed a PLCS DEX specifically targeted at aviation maintenance [33]. The Aviation Maintenance DEX focuses on sharing information in four categories:

1. Historical maintenance activities;
2. Activities that, while not maintenance-specific, may impact future maintenance (e.g., flying sorties);
3. Estimation of system state (e.g., fault state, and serviceability); and
4. Activities affecting product inventories.

The PLCS architecture uses multiple DEXs to support information exchange between agents needing the information. DEXs related to the Aviation Maintenance DEX include:

1. Product as-designed structure;
2. Specific product as-delivered structure;
3. Maintenance plan;
4. Faults related to the product; and
5. Specific information on maintenance tasks.

ISO also provides a collection of standards focusing on condition monitoring and diagnosis of machines [34]. These standards are developed by the technical committee on mechanical vibration and shock and focus on test design, measurement, and data processing focused specifically in these areas.

IV. STANDARDIZING PHM

In this paper, we have been focusing on standards for information exchange. We recognize that standards are also necessary for communications, form-fit-function of devices, physical interfaces, timing, calibration, etc. Many standards exist to support such elements, and such standards also need careful consideration when building a PHM system. In the previous section, we reviewed the principal standards supporting maintenance and diagnosis and suggested how these standards might support the PHM enterprise. In this section, we will discuss the key PHM characteristics that are present or that need to be included in standards to meet PHM requirements.

A. PHM Characteristics in Current Standards

Fundamentally, PHM systems incorporate functions of condition monitoring, state assessment, fault or failure diagnostics, failure progression analysis, predictive diagnostics (i.e., prognostics), and maintenance support. Thus these functions must be supported in any collection of PHM-related standard. Specifically, PHM-related standards must be able to represent and exchange measured, observed, and inferred information about the target system and its operational environment, information about the current state as well as either an estimate of some future state or an estimate of when some target state might be reached, historical information about the operation and maintenance of the target system, and various models of the system.

The OSA-CBM standard provides a detailed object model, represented in UML that identifies key data items, objects, and their relationships within a CBM system. Note that the algorithms are referenced via MIMExtTypes which are extensions to MIME types. No facility is provided for *standard* algorithm specification. In addition, OSA-CBM provides detailed facilities for exchanging logical propositions about the system. These are supported by detailed health assessment data items that include health level of the system and health grade of an item.

The IEEE standards provide sound support for information exchange supporting the process of test and diagnosis of the target system. The AI-ESTATE standard provides a foundation for diagnostic assessment and includes four alternatives for diagnosis—static fault trees (or decision trees), D-matrix-based systems (e.g., dependency models), logic-based models (e.g., rule-based expert systems), and Bayesian networks. All four alternatives have been demonstrated to provide effective and accurate diagnostics. In addition, the standard has been defined to address *all* test environments, thus there is no implicit or explicit focus on ATS. As stated earlier, they do not currently provide facilities for prediction and are based on discrete test and diagnosis outcomes.

The SIMICA family of standards (including Test Results and MAI) focuses on historical information but provide a means for using that information to improve both diagnostics and prognostics. Recognizing that PHM systems based entirely on discrete, outcome-based testing will be severely limited in their ability to predict future states, we find that the Test Results standard, while providing outcome-based data, also provides a method for capturing actual measurement data. This standard is oriented towards automatic test systems; however, the supporting information model provides a means for transitioning to a real-time health monitoring system as well.

The MAI standard also provides both an XML schema and an information model. MAI focuses on the maintenance process rather than the test process; therefore, it is easily generalizable to PHM.

B. Enhancements Needed to Current Standards

The primary challenge facing SCC20 is in determining how best to extend or adapt current standards to PHM. We believe that, at a minimum, the following must be provided as enhancements or additions to the current set of standards:

1. A means for representing graded health information rather than limiting diagnostics to discrete outcomes.
2. Given the ability to represent graded health information, a means to "roll up" failure progression information to higher levels in the system hierarchy.
3. Relaxation or augmentation of the outcome-based approach to diagnosis to support state estimation based on real-valued test results.
4. The ability to support periodic measurements and correlation between time series.
5. Incorporation of usage, operational, and environmental data in performing state assessment and diagnosis.
6. Representation of failure progression/degradation information for specific systems.
7. A framework for integrating and combining information from multiple models and model types (e.g., physics-based, reliability-based, and data driven) to exploit the specific advantages of each type.

As a specific example, SCC20 is currently exploring a change to the AI-ESTATE standard that would address the need for capturing "grayscale" (i.e., graded) health information. Including grayscale health supports reasoning about current state of degradation and projecting future failure progression. It is also applicable to incipient fault detection. To address grayscale health, changes will be required in the Common Element Model to specify that a diagnosis outcome need not be discrete as well as the Dynamic Context Model to record the inferred grayscale

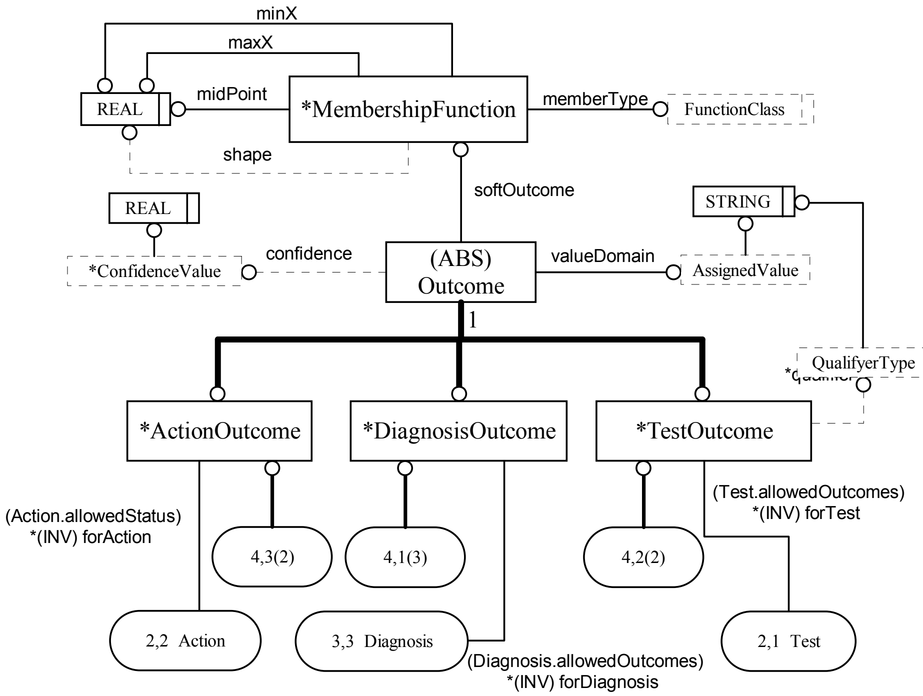

Figure 2. Soft Outcome Definition for PHM in AI-ESTATE

health estimate. In addition, at least one of the inference models (i.e., fault tree, D-matrix, logic, and Bayes) will have to be updated to indicate inferences of grayscale health from test results or outcomes.

Figure 2 illustrates one possible change to the definition of the Outcome entity in the Common Element Model. The only difference from the definition in [35] is the addition of the "softOutcome" attribute. The purpose of this attribute is to associate a soft or gray-scale function to the outcome where the domain of the function is specified but the range is [0, 1]. Six types of functions have been identified—triangular, trapezoidal, radial (e.g., Gaussian), hard limiter, linear threshold, and sigmoidal. The first three correspond to common "membership" functions from fuzzy logic, and the latter three correspond to common transfer functions for function approximators such as neural networks. The attributes, "minx," "maxX," "midpoint," and "shape" provide key parameters for the function. The minimum and maximum X values specify the domain of the function. All of the functions have a point about which the functions are (usually) symmetric. This is identified with "midpoint." Finally, the "shape" parameter is specific to the type of function. For example, for the radial function, the shape parameter represents the spread (or variance) of the function where, for the sigmoid function, it represents the slope at the point of inflection. Given the soft outcome, a corresponding attribute can then be added to "ActualOutcome" in the AI-ESTATE Dynamic Context Model to assign a value to the outcome based on the associated function.

V. CONCLUSION

Two of the primary reasons for standardization are to reduce cost by improving interoperability and minimizing repeated design of similar systems. The IEEE SCC20 standards focus on promoting information interoperability between components of a test or health monitoring system. The emphasis by the DOD on acquisition reform based on commercial standards for ATS, combined with declining budgets mandates the need for more affordable health management system development and operation. Cost must be reduced. Interoperability must be achieved. Information must be shared.

The cost of reactive maintenance has become prohibitive, especially for complex systems. Even with the development of comprehensive standards focusing on interoperability and reuse, the way systems are maintained must and is changing. Providers are required to implement interoperable systems based on these standards. With the recent focus on CBM and prognostics, the need exists for exchanging more robust information in a timely way that will enable identifying and correcting a fault before it occurs. As with traditional testing, standards for CBM and PHM are also required.

Technological advances in CBM and PHM have identified core types of information needed for health monitoring systems. What we have found is that there is a strong overlap between the type of information needed for health monitoring and the type of information used in traditional diagnosis. Therefore, the IEEE has been working to identify and expand its existing test and diagnostic standard to address PHM requirements. It is likely new standards will also emerge where enhancing current standards would constitute a "force fit." Fortunately, SCC20 is well-positioned to identify and address those challenges.

REFERENCES

[1] Kalgren, Patrick, Carl Byington, Michael Roemer, and Matthew Watson, "Defining PHM, A Lexical Evolution of Maintenance and Logistics," *IEEE AUTOTESTCON 2006 Conference Record*, Anaheim, California, September 2006, pp. 353–358.

[2] Hess, Andrew, "Real Prognostics—Challenges, Issues, and Lessons Learned: Chasing the Big 'P'," First International Forum on Integrated System Health Engineering and Management in Aerospace, NASA, Napa Valley, CA, November 7–10, 2005.

[3] Roemer, Michael, Carl Byington, Gregory Kacprzynski, and George Vachtsevanos, "An Overview of Selected Prognostic Technologies with Reference to an Integrated PHM Architecture," First International Forum on Integrated System Health Engineering and Management in Aerospace, NASA, Napa Valley, CA, November 7–10, 2005.

[4] Vachtsevanos, George, Frank Lewis, Michael Roemer, Andrew Hess, and Biqing Qu, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*, John Wiley & Sons, Inc., 2006.

[5] Jata, K. V. and T. A. Parthasarathy, "Physics of Failure," First International Forum on Integrated System Health Engineering and Management in Aerospace, NASA, Napa Valley, CA, November 7–10, 2006.

[6] Kalgren, Patrick, Mark Baybutt, Antonio Ginart, Chris Minnella, Michael Roemer, and Thomas Dabney, "Application of Prognostic Health Management in Digital Electronic Systems," *Proceedings of the 2007 IEEE Aerospace Conference*, Big Sky, MT, March 2007.

[7] Scott, Andrew, "Electro-Mechanical Diagnostics/Prognostics," *IEEE AUTOTESTCON 2007 Conference Record*, Baltimore, MD, September 2007, pp. 340–348.

[8] Klion, J., *Practical Electronic Reliability Engineering*, New York: Van Nostrand Reinhold, 1992.

[9] Groer, P. G., "Analysis of Time-to-Failure with a Weibull Model," *Proceedings of the Maintenance and Reliability Conference*, *MARCON 2000*, Knoxville, TN,

[10] Carey, M. B. and R. H. Koenig, "Reliability Assessment Based on Accelerated Degradation: A Case Study," *IEEE Transactions on Reliability*, Vol. 40, No. 5, December 1991, pp. 499–506.

[11] Luo, M., D. Wang, M. Pham, C. B. Low, J. B. Zhang, D. H. Zhang, and Y. Z. Zhao, "Model-Based Fault Diagnosis/Prognosis for Wheeled Mobile Robots: A Review," *Proceedings of the 31st Annual Conference of IEEE Industrial Electronics Society*, November 2005, pp. 2267–2272.

[12] Khiripet, Noppadon, *An Architecture for Intelligent Time Series Prediction with Causal Information*, PhD Thesis, Department of Electrical Engineering, Georgia Institute of Technology, 2001.

[13] Sheppard, J. W., S. G. W. Butcher, and R. Ramendra, *Electronic Systems Bayesian Stochastic Prognosis: Algorithm Development*, Technical Report JHU-NISL-07-002, September 2007.

[14] Bengio, Y. and P. Frasconi, "Diffusion of Context and Credit Information in Markovian Models," *Journal of Artificial Intelligence Research*, 3:249–270, 1995.

[15] Bengio, Y. and P. Frasconi, "Input-Output HMMs for Sequence Processing," *IEEE Transactions on Neural Networks*, Vol. 7, No. 5, September 1996, pp. 1231–1249.

[16] Machinery Information Management Open Standards Alliance (MIMOSA), *Open Systems Architecture for Condition Based Maintenance (OSA-CBM) Primer*, August, 2006.

[17] Machinery Information Management Open Standards Alliance (MIMOSA), *Open Systems Architecture for Condition Based Maintenance (OSA-CBM) UML Specification*, v3.1, http://docs.oasis-open.org/plcs/dexlib/R1/dexlib/data/dex/aviation_maintenance/home.htm, December 30, 2006.

[18] IEEE Std 1641-2004, *IEEE Standard for Signal and Test Definition*, Piscataway, New Jersey: IEEE Standards Association Press, 2004.

[19] IEEE Std 1671-2006, *IEEE Trial Use Standard for Automatic Test Markup Language (ATML) for Exchanging Automatic Test Information via eXtensible Markup Language (XML)*, Piscataway, New Jersey: IEEE Standards Association Press, 2006.

[20] IEEE Std 1232-2002, *IEEE Standard for Artificial Intelligence Exchange and Service Tie to All Test Environments (AI-ESTATE)*, Piscataway, New Jersey: IEEE Standards Association Press, 2002.

[21] IEEE P1636, *Draft IEEE Trial Use Standard for Software Interface for Maintenance Information Collection and Analysis (SIMICA)*, D1.6, Piscataway, New Jersey: IEEE Standards Association Press, 2008.

[22] IEEE Std 1636.1-2007, *IEEE Trial Use Standard for Software Interface for Maintenance Information Collection and Analysis (SIMICA): Exchanging Test Results and Session Information via the eXtensible Markup Language (XML)*, Piscataway, New Jersey: IEEE Standards Association Press, 2007.

[23] IEEE P1636.2, *Draft IEEE Trial Use Standard for Software Interface for Maintenance Information Collection and Analysis (SIMICA): Exchanging Maintenance Action Information via the eXtensible Markup Language (XML)*, D3.0, Piscataway, New Jersey: IEEE Standards Association Press, April 2008.

[24] ISO 10303-11:1994, *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 11: Description Methods: The EXPRESS Language Reference Manual*, Geneva, Switzerland: International Organization for Standardization, 1994.

[25] ISO 10303-21:1994, *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 21: Implementation Methods: Clear Text Encoding of the Exchange Structure*, Geneva, Switzerland: International Organization for Standardization, 1994.

[26] ISO 10303-28:2007, *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 28: XML Representation of EXPRESS Schemas and Data using XML Schemas*, Geneva, Switzerland: International Organization for Standardization, 2007.

[27] W3C, *Web Services Description Language (WSDL)*, v1.1, W3C Note, March 15, 2001, http://www.w3.org/TR/wsdl.

[28] Sheppard, John W. and Jonas Åstrand, "Modeling Diagnostic Constraints with AI-ESTATE, *IEEE AUTOTESTCON 1995 Conference Record*, Atlanta, GA, September 1995, pp. 528–533.

[29] Kaufman, Mark A. and John W. Sheppard, "Bayesian Modeling: An Amendment to the AI-ESTATE Standard," *IEEE AUTOTETSCON 2005 Conference Record*, Orlando, FL, September 2005, pp. 424–430.

[30] Ralph, John, "A Proposed Comprehensive Architecture Utilizing the Automatic Test Markup Language (IEEE 1671 and 1636.1)," *AUTOTESTCON 2007 Conference Record*, Baltimore, MD, September 2007, pp. 190–196.

[31] Wilmering, Timothy and John Sheppard, "Ontologies for Data Mining and Knowledge Discovery to Support Diagnostic Maturation," *Proceedings of the 18th International Workshop on Principles of Diagnosis (DX-07)*, Nashville, TN, pp. 210–217.

[32] ISO 10303-239:2005, *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 239: Application Protocol: Product Life Cycle Support*, Geneva, Switzerland: International Organization for Standardization.

[33] Organization for the Advancement of Structured Information Standards (OASIS), *Product Life Cycle Support (PLCS) Aviation Maintenance Data Exchange Specification (DEX)*, rev 1.145, http://docs.oasis-open.org/plcs/dexlib/R1/dexlib/data/dex/aviation_maintenance/home.htm, March 10, 2008.

[34] ISO 13374-1:2003, *Condition Monitoring and Diagnostics of Machines—Data Processing, Communications and Presentation—Part 1: General Guidelines*, Geneva, Switzerland: International Organization for Standardization.

[35] IEEE P1232, *Draft IEEE Standard for Artificial Intelligence Exchange and Service Tie to All Test Environments (AI-ESTATE)*, D1.0, Piscataway, New Jersey: IEEE Standards Association Press, 2008.