International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 3, March - 2013

Perfunctory Issues Errand to Superfluous Effectual Prophetic System

Deepak Gaur[1,] Richa Gaur[2]

[# 1] Assistant Professor, Department of Mechanical Engineering

[#2] Assistant Professor, Department of Electronics & Communication Engineering

J.M.I.T, Radaur, Yamunanagar, Haryana, India

Abstract

Defy for prophetic technologies from the viewpoint of both system chic and consumer will be addressed. However, there are still methodological and technological matters that must be dealt with to provide more effective prophetic systems.These defy include implementing optimum sensor systems and settings, selecting applicable prophetic methods, addressing prognostic uncertainties, and estimating the cost-benefit implications of prophetic implementation. The explore prospects are summarized as well.

"1. Introduction"

Many names have been used to describe prophetic. For example, the prophetic technology used in U.S. Army rotorcraft was called the Health and Usage Monitoring System (HUMS) [4]. In aerospace, Integrated Vehicle Health Management (IVHM) was the term given for prophetic of reusable rockets, and later for various space applications used by NASA [5]. In other fields of the military, several prophetic labels have been defined, including the Aircraft Condition Monitoring System (ACMS), the Engine Monitoring System (EMS) [6], [7], the Integrated Diagnostics and Prophetic System (IDPS) [8], and the Integrated Condition Assessment System (ICAS) [8]. In the Joint Strike Fighter (JSF) program, the name Prophetic and Health Management (PHM) was adopted [9], [10]. Since then, prophetic technology has become an area of flourishing international research. Many prophetic practices have been conducted in various engineering applications, such as in the defense and military industry [4]–[11], the aerospace industry [12]–[14], wind power systems [15], civil infrastructure [2], batteries [16], mechanical manufacturing [17]–[23], consumer electronics, and computers [24]–[31]. For aerospace systems, Pratt & Whitney implements advanced prophetic and health management systems in their engine for the F135 multipurpose fighter [12]. Similar diagnostic and health monitoring systems are included in the Airbus A380 and Boeing 787 as well. For electronics systems, physics-of-failure (PoF) based methods have been shown to be effective for prophetic. The PoF approach uses a product's actual environmental and operational loads, together with PoF models, to calculate the accumulated damage, and predict the RUL of the product [24], [25]. The PoF-based approach has been successfully applied to notebook computers [26], the electronics in the NASA space shuttle solid rocket booster [27], commercial off-the-shelf (COTS) devices [28], and flash memory [29]. On the other hand, data-driven methods are also widely used in electronics prophetic. Prophetic has been implemented using a variety of techniques. The most important techniques are Markov chains, stochastic processes, and time series analysis. Some applications in electronics where data-driven approaches have been used for RUL estimation include computer servers [32], global positioning systems [33], avionics [34], and power electronics devices (IGBTs) used in avionics [35]. A fusion prophetic approach, which combines data-driven and PoF-based methods, has been developed to estimate the RUL of electronic components and systems [36], [37]. From all the applications that use prophetic, we can see that implementing prophetic generates many benefits. In this paper, the key benefits of prophetic are presented in Section II. The current barriers and technological defy involved in implementing prophetic are discussed in Section III, and research opportunities are discussed in Section IV.

"2.Defy for the execution of Prophetic''

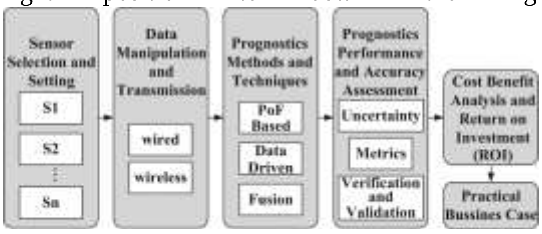
The implementation of a prophetic system generally includes several key processes and technologies, such as data acquisition, data processing, fault diagnostics, prophetic, and decision reasoning (see Fig. 3). Prophetic system implementation has its own life cycle process, including design and development, test and evaluation, verification and validation, production, and application [71].Although the list of the major benefits of prophetic is impressive, prophetic technologies are still not mature enough. The

ISSN: 2278-0181
Vol. 2 Issue 3, March - 2013

following subsections discuss defy facing the implementation of prognostic.

"3. Employing most favorable Sensor assortment and Localization"

Data collection is an essential part of prophetic. It often requires the use of sensor systems to measure the environmental, Inaccurate measurements resulting from improper sensor selection and localization (e.g., making sure the sensor is in the right position to obtain the right

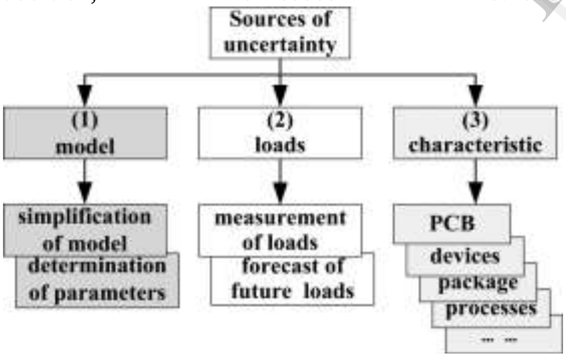


"Figure3. Major gears of prophetic execution"

data) or inadequate measurements can degrade the prognostic performance. An approach is also needed [72] to conduct trade-offs for various types of sensors (pressure, speed, thermal, humidity, optical, magnetic, electric, sound, gas) in terms of precision, sensitivity, stability, power consumption, reliability, and sensor networking. Knowledge of the appropriate performance parameters or precursors to be monitored will help in the selection of the right sensor for the product. The sensors that are selected should be able to accurately measure the change in the parameters linked to the critical failure mechanisms. The successful implementation of PHM relies on data from the system. When sensors are used to collect these data, the possibility of sensor failures must also be taken into account. Some strategies to improve the reliability of sensors have been presented, such as using multiple sensors to monitor the same system (i.e., redundancy), and implementing sensor validation to access the integrity of a sensor system and adjust or correct it as necessary [13].

"4. Selecting Applicable Prophetic Methods"

When data are transmitted, it is necessary to consider noise and interference in data obtained from sensors, which can influence prophetic performance and accuracy. Therefore, the data used for prophetic need to be preprocessed (through processes such as data filtering and reduction). There are many filters, but a priority selection process has not yet been developed. Generally, methods for prophetic can be grouped into data-driven methods, PoF-based methods, and fusion methods [1], [75], [76]. Data-driven methods are based on machine-learning techniques, and statistical pattern recognition. PoF-based methods utilize knowledge of a product's life cycle loading and failure mechanisms to assess its reliability. The fusion prophetic approaches combine PoF-based and data-driven approaches [32]–[37]. Prophetic methods can vary widely for different types of products and failure modes. Proper selection of prophetic methods for a particular domain is a key factor that determines whether a prophetic system will be effective. Data-driven methods are based on machine-learning and statistical techniques. These algorithms can be implemented at the system, subsystem, or component levels [77]. In general, machine-learning techniques can be classified into three categories: supervised, unsupervised, and semi-supervised learning approaches. The training data used by supervised and semi-supervised learning need to be classified correctly, which might affect the confidence level of the algorithm. Additionally, optimization and search methods are often employed in these data-driven methods, and their computational complexity and tractability are critical for efficient and effective algorithms. On the other hand, these data-driven methods often address only anticipated faults, in which a fault "model" is a construct or a collection of constructs, such as artificial neural networks (ANNs), support vector machines (SVMs), expert systems, etc., that must be trained first with known prototype fault patterns (data) [2]. For unsupervised learning approaches, the given data have no predefined classes, and do not include any labeled data. The algorithm using unsupervised learning finds clusters by itself from its unlabeled data. There are different ways of dividing the data into clusters, and many different ways to prescribe clusters. The same data might be differently clustered according to its clustering algorithm. Acquisition of labeled input data is costly because an expert needs to distinguish the class of data. Statistical techniques are divided into parametric and non-parametric methods based on whether the information regarding the distribution of the data is assumed or not. These methods are very mature [78]. However, a large amount of failure data is needed to implement these approaches to allow for analysis, and this can be more problematic if the monitored systems exhibit intermittent faults. Most data-driven approaches depend on historical (i.e., training) system data to determine correlations, establish patterns, and evaluate data trends leading to failure. In many case there is an insufficient amount of historical or operational data to obtain health estimates, and determine trend thresholds for failure prophetic. This condition is true, for example, for stored, standby, and non-operating systems, which are nevertheless subject to environmental stress conditions. There are also defy in systems where failures are infrequent [2]. PoF-based prognostic methods utilize knowledge of a product's life cycle loading and failure mechanism models, control models, or some other phenomenologically descriptive models of the system to assess product reliability, and estimate the system's remaining life [1], [75]. The advantage of a PoF-based method is often its ability to isolate the root cause(s) that contribute to system failure [77]. However, sufficient information about the product is needed. For example, in PoF models, the materials, geometry, and operational and environmental conditions are required. In complex systems, these parameters may be difficult to obtain. The development of models requires some knowledge of the underlying physical processes that lead to system failure, but in complex systems it is difficult to create dynamic models representing the multiple physical processes occurring in the system [1]. This is one of the limitations of PoF-based approaches. As noted, a requirement of the PoF-based approach is that system specific knowledge, such as geometry and material composition, is necessary but may not always be available. Further, failure models, or graph-based models are not suitable for the detection of intermittent system behavior because they are modeled for specific degradation mechanisms, or for the diagnosis of specific faults, respectively. In addition, PoF-based methods

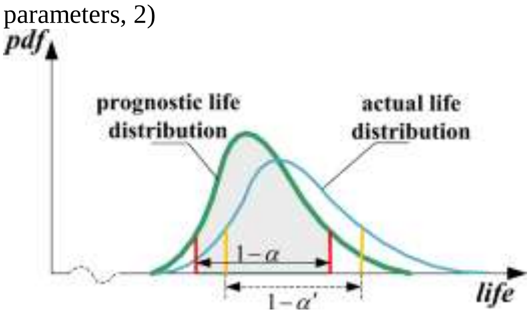


"Figure4. Uncertainties in PoF-based electronic prophetic"

cannot be used on every component in a complex system due to technical and economic considerations. Pecht *et al.* [32]–[37], [79] developed a fusion prophetic approach that combines the PoF and the data-driven approaches to estimate the RUL of a product in its actual life cycle conditions. The combination of the PoF approach and the data-driven approach provides a means to correlate data trends and precursor events with failure mechanisms, and also to isolate the root cause of failure. The data-driven approach is used to carry out product diagnostics by anomaly detection, while information from the PoF models, product standards, and specifications is incorporated into the data-driven techniques for estimation of RUL. The parameters causing anomalous behavior are isolated using data-driven techniques or knowledge of the PoF. These parameters are used to identify the failure mechanisms and relevant PoF models, and for RUL estimation. This fusion method therefore combines the strengths of the individual approaches to provide more accurate diagnostics and estimation of RUL, as well as information regarding the parameters that indicate product failure, thereby helping with root-cause analysis.

"5. Dealing with Prophetic vague and evaluating Prophetic precision"

Another major challenge for the use of prophetic is the need to develop methods that are capable of handling real world uncertainties that lead to inaccurate predictions. For example, Gu *et al.* [74] studied various sources of prognostic uncertainty. In their study, they found that measurement inaccuracies of the sensors were one of the main sources leading to uncertainty in their prophetic application. Prophetic errors can lead to unnecessary preventive maintenance due to underestimation of system remaining life (false alarms) on the one hand, and unnecessary system failures and even catastrophic events due to overestimation of RUL on the other hand. Although some methods for uncertainty analysis and assessment using PoF models have been developed, there are several defy to the implementation of uncertainty into prophetic [80], [81]. Fig. 4 shows some sources of uncertainty for PoF-based electronic prophetic [2]. These uncertainties are generally grouped into three different categories: 1) model (PoF and accumulative damage) uncertainty caused by model simplification and model parameters, 2)



"Figure 5. Schematic illustration of prognostic accuracy concept"

[2]. measurement and forecast uncertainty induced by life cycle environmental and operational loads, and 3) uncertainties with the characteristic parameters (geometry and materials) of products mainly caused by the production process. These uncertainties can lead to the significant deviation of

prophetic results from the actual situation. For data-driven methods, long prognostic distance (as shown in Fig. 2.) prediction of RUL or time to failure increases the uncertainty bounds due to various sources, such as measurement or sensor errors, future load and usage uncertainty, model assumptions and inaccuracies, loss of information due to data reduction, prediction under conditions that are different from the training data, and so on [1]. Hence, the development of methods that can be used to describe the uncertainty bounds and confidence levels for values falling within the confidence bounds is required. Another research area is uncertainty management, where methods are being investigated to reduce the uncertainty bounds by using system data as more data become available [82], [83]. Prognostic accuracy assessment technologies are necessary for building and quantifying the confidence level of a prophetic system. Methods to impartially evaluate the effectiveness and accuracy of prophetic are required. As mentioned above, uncertainties can affect the prediction of actual failure time for field products, which are characterized by an actual life distribution interval rather than an actual life single-point value [84], [85]. On the other hand, with the consideration that the geometry and material parameters of field products cannot be measured one by one, and that future loads are inherently uncertain, the prognostic life of PoF models should be expressed as a distribution (i.e., prognostic life distribution). Fig. 5 illustrates the difference between an actual life distribution and a prognostic life distribution. An ideal prognostic accuracy and effectiveness case is one where the prognostic life probability density function (PDF) is narrow (i.e., has a small distribution span) and is fit to the actual life PDF (i.e., a prognostic distribution curve consistent with the actual distribution curve).There is no general agreement as to an appropriate and acceptable set of metrics that can be employed effectively to assess the technical performance of prognostic systems [84]. Leão [87] proposed a set of metrics to evaluate the performance of prophetic algorithms, including prophetic hit score, false alarm rate, missed estimation rate, correct rejection rate, prophetic effectivity, etc. Saxena [88] also suggested a list of metrics to assess critical aspects of RUL predictions, such asprognostic horizon, prediction spread, relative accuracy, convergence, horizon/precision ratio, etc. Although efforts have been made to cover most PHM requirements, further refinements in concepts and definitions are expected as prophetic matures.

"6. Scrutinizing expenditure-profit of Prophetic relevance"

The benefits of prophetic are many, but prophetic also costs money in terms of acquisition and installation costs, implementation costs, and changes in business practices. Apart from those PHM costs, the cost of re-design of host product can be a big investment. For example, to deploy a sensor and microprocessor on a ball bearing or gearbox, the original cables need to be re-wired to supply power to the sensor. The casting must also be re-designed to take in the sensor and protect it from the environment. These implementation costs need to be accounted for. If there is no economic benefit (or too high of a perceived risk, particularly regarding consequential damages), system vendors may not wish to implement PHM. Cost-benefit analysis (CBA) and quantitative assessment are therefore essential for assessing the effectiveness of prophetic [89]–[92]. There are many financial metrics that can be used in a cost benefit quantitative analysis, including net cash flow, cumulative cash flow, payback, return on investment (ROI), net present value (NPV), and internal rate of return (IRR) [45], [93].Among all these metrics, ROI is one of the most selective metrics. ROI tells us the rate of return on the investment in prophetic, which enables the investment in prophetic to be compared with other competing investments [63], [88]. The benefits as mentioned above help the prospective user of prophetic understand the practical drivers of this technology, but the user still needs more information to justify their investment in the technology. The information that is most useful to the user is a calculated ROI for their particular system that provides a financial assessment of the benefit of the investment. ROI involves an analysis of the cost avoidances made possible by using prophetic technology against the costs associated with the development, manufacture, installation, and implementation of prophetic technology in selected systems [89]. The determination of ROI allows system managers to include quantitative, readily interpretable results in their decision making. ROI analysis may be used to select between different types of prophetic technology, optimize the use of a particular prophetic approach, or determine whether to adopt prophetic versus more traditional maintenance approaches. For instance, the Pacific Northwest National Laboratory (PNNL) conducted an initial CBA assessment to aid in decisions about whether or not to develop a prototype prophetic system for the AGT1500 gas turbine engine on the M1 Abrams Tank [13]. The results of the analysis indicated that the development and deployment of an engine prophetic system with approximately a dozen auxiliary sensors (thermodynamic and vibration sensors installed via a wiring harness) would result in a benefit-to-cost ratio of about 11:1. One of the most significant defy when conducting a cost-benefit analysis is the iterative process of selecting the appropriate prophetic technology based on assumptions of estimated benefits. For example, a given prognostic technology may be effective for assessing five of the eight possible failure modes for batteries; this technology would account for 62.5% of the failures, but would cost $200 per battery to implement. Another technology may be effective for assessing the other three failure modes, accounting for 35% of the failures, but costing $150 per battery to implement [93]. This technology allows for the evaluation of technologies as a function of cost versus the effectiveness of the technology, because not all technologies have an equivalent capability. For example, Feldman *et al.* [94] analyzed the ROI of a precursor-to-failure prophetic approach relative to unscheduled maintenance, but it may not be consistent with the ROI of using life consumption monitoring methods (LRU independent methods), and is not specific to a particular precursor to failure device. Another challenge when conducting CBA is determining what values to select for all of the variables in the CBA model. The Applied Research Laboratory (ARL) Trade Space Visualizer (ATSV) provides the ability to iteratively solve for all of the statistically dependent and independent variables in the CBA model, and visually present all of the data for assessment. This tool is used to analyze the benefits of implementing battery prophetic on military ground combat vehicles [93]. The third challenge for determining ROI in prophetic is that it is difficult to quantify the benefits of prophetic results. Standard measures of performance need to be well defined in order to assess and justify the anticipated ROI [59], [94]–[96]. The cost benefit is related not only to prophetic opportunity, the warning lead-time interval, and user requirements, but also to affordable cost and acceptable safety risk. Additionally, the overall logistics support system, spare parts supply, supply chain management, and other related resources are also related to prophetic cost benefit. This system introduces a challenging multi-objective and multi-attribute tradeoff, and a complex decision-making problem that must be dealt with.

“8.Conclusion”

In this paper, we have provided explanations of some of the key benefits of prophetic in terms of system life-cycle processes. It is important to highlight the advancements in the field of PHM that will enhance the practical engineering applications of prophetic technologies. However, there are still methodological and technical issues that must be dealt with to provide more effective prophetic systems. In this paper research can be in establishment of field prophetic system design and development guidelines, including hardware-related sensor selection (e.g., sensor types, sensor performance, sensitivity, stability, power consumption, reliability, and sensor networking), wireless or wired data transmission, software-related diagnostics, prophetic, and decision reasoning algorithms and programs. Investigate methods and procedures to cost-effectively integrate prophetic into existing systems. Determine how to integrate prophetic system design with the host system design process. Develop metrics and methods to impartially measure and evaluate the performance of a prophetic system.Conduct more studies on the life cycle return on investment attached to the implementation of prophetic technologies.

9. References

[1] J. D. Kozlowski, “Electrochemical cell prophetic using online impedance measurements and model-based data fusion techniques,” in *Proceedings of 2003 IEEE Aerospace Conference*, Big Sky, Montana, March 8–15, 2003, pp. 3257–3270.
[2] W. Hardman, “Mechanical and propulsion systems prophetic: U.S. navy strategy and demonstration,” *JOM*, vol. 56, no. 3, pp. 21–27, 2004.
[3] G. J. Kacprzynski, A. Sarlashkar, and M. J. Roemer *et al.*, “Predicting remaining life by fusing the physics of failure modeling with diagnostics,” *JOM*, vol. 56, no. 3, pp. 29–35, 2004.
[4] Y. G. Li and P. Nikitsaranont, “Gas path prognostic analysis for an industrial gas turbine,” *Insight: Non-Destructive Testing and Condition Monitoring*, vol. 50, no. 8, pp. 428–435, 2008.
[5] W.Wang, “A model to predict the residual life of rolling element bearings given monitored condition monitoring information to date,” *IMA Journal of Management Mathematics*, vol. 13, no. 1, pp. 3–16, 2002.
[6] A. H. Christer, W. Wang, and J. Sharp, “A state space condition monitoring model for furnace erosion prediction and replacement,” *European Journal of Operational Research*, vol. 101, no. 1, pp. 1–14, 1997.
[7] W. Wang, P. A. Scarf, and M. A. J. Smith, “On the application of a model of condition based maintenance,” *Journal of the Operational Research Society*, vol. 51, no. 11, pp. 1218–1227, 2000.
[8] W.Wang andW. Zhang, “An asset residual life prediction model based on expert judgments,” *European Journal of Operational Research*, vol. 188, no. 2, pp. 496–505, 2008.
[9] J. Gu, D. Barker, and M. Pecht, “Prophetic implementation of electronics under vibration loading,” *Microelectronics Reliability*, vol. 47, no. 12, pp. 1849–1856, 2007.

[10] A. Ramakrishnan and M. Pecht, "A life consumption monitoring methodology for electronic systems," *IEEE Trans. Components and Packaging Technologies*, vol. 26, no. 3, pp. 625–634, 2003.
[11] N. Vichare, P. Rodgers, V. Eveloy, and M. G. Pecht, "In-situ temperature measurement of a notebook computer—A case study in health and usage monitoring of electronics," *IEEE Trans. Device and Materials Reliability*, vol. 4, no. 4, pp. 658–663, 2004.
[12] S. Mathew, D. Das, and M. Osterman *et al.*, "Virtual remaining life assessment of electronic hardware subjected to shock and random vibration life cycle loads," *Journal of the Institute of Environmental Sciences and Technology*, vol. 50, no. 1, pp. 86–97, 2007.
[13] V. Rouet, F. Minault, G. Diancourt, and B. Foucher, "Concept of smart integrated life consumption monitoring system for electronics," *Microelectronics Reliability*, vol. 47, no. 12, pp. 1921–1927, 2007.
[14] B. Sun, Y. Zhao, and W. Huang *et al.*, "Case study of prognostic and health management methodology for electronics," (in Chinese) *Systems Engineering and Electronics*, vol. 29, no. 6, pp. 1012–1016, 2007.
[15] C.Wu,C. Yang, S.Lo, N. Vichare, E. Rhem, andM. Pecht, "Automatic data mining for telemetry database of computer systems," *Microelectronics Reliability*, vol. 51, no. 2, pp. 263–269, 2011.
[16] G. Niu, S. Singh, S. W. Holland, and M. Pecht, "Health monitoring of electronic products based on Mahalanobis distance and Weibull decision metrics,"*Microelectronics Reliability*, vol. 51, no. 2, pp. 279–284, 2011.
[17] L. Lopez, "Advanced electronic prophetic through system telemetry and pattern recognition methods,"*Microelectronics Reliability*, vol. 47, no. 12, pp. 1865–1873, 2007.
[18] D. W. Brown, P. W. Kalgren, C. S. Byington, and J. R. Roemer, "Electronic prophetic—A case study using global positioning system (GPS)," *Microelectronics Reliability*, vol. 47, no. 12, pp. 1874–1881, 2007.
[19] C. S. Byington, P. W. Kalgren, B. K. Dunkin, and B. P. Donovan, "Advanced diagnostic/prognostic reasoning and evidence transformation techniques for improved avionics maintenance," in *Proceedings of 2004 IEEE Aerospace Conference*, Big Sky, Montana, March 6–13, 2004, pp. 3424–3434.
[20] B. Saha, J. Celaya, P. Wysocki, and K. Goebel, "Towards prophetic for electronics components," in *Proceedings of the 2009 IEEE Aerospace Conference*, Big Sky, Montana, March 7–14, 2009, pp. 1–7.
[21] M. Pecht and J. Gu, "Prophetic-based product qualification," in *Proceedings of 2009 IEEE Aerospace Conference*, Big Sky, Montana, March 7–14, 2009, pp. 1–11.
[22] R. Jaai and M. Pecht, "Fusion prophetic," in *Proceedings of Sixth DSTO International Conference on Health & Usage Monitoring*, Melbourne, Australia, March 9–12, 2009, pp. 1–12.
[23] W. Denson, "History of reliability prediction," *IEEE Trans. Reliability*, vol. 47, no. 3-SP, pp. 321–328, 1998.
[24] P. Lall, M. Pecht, and E. Hakim, *The Influence of Temperature on Microelectronic Device Reliability*. Boca Raton, FL: CRC Press, 1997.
[25] M. J. Cushing, D. E. Mortin, T. J. Stadterman, and A.Malhotra, "Comparison of electronics-reliability assessment approaches," *IEEE Trans. Reliability*, vol. 42, no. 4, pp. 542–546, 1993.
[26] S. L. Dreyer, "Autonomic logistics—Developing an implementation approach for an existing military weapon system," *IEEE Instrumentation and Measurement Magazine*, vol. 9, no. 4, pp. 16–21, 2006.
[27] S. Trimble, "JSF industry team seeks new business model for logistics," *Jane's Defence Weekly* April 21, 2006 [Online]. Available: http://articles.janes.com/articles/Janes-Defence-Weekly-2006/JSFteam- seeks-new-logistics-business-model.html 334 IEEE TRANSACTIONS ON RELIABILITY, VOL. 61, NO. 2, JUNE 2012
[28] S. O. John, *Statistical Process Control*, Sixth ed. Oxford: Butterworth- Heinemann, 2008.
[29] G. Bird, M. Christensen, and D. Lutz *et al.*, "Use of integrated vehicle health management in the field of commercial aviation," in *Proceedings of NASA ISHEM Forum*, Napa, California, November 7–10, 2005, pp. 1–12.
[30] J. Banks, K. Reichard, and E. Crow *et al.*, "How engineers can conduct cost-benefit analysis for PHM systems," *IEEE Aerospace and Electronic Systems Magazine*, vol. 24, no. 3, pp. 22–30, 2009.