

Some Diagnostic and Prognostic Methods for Components Supporting Electrical Energy Management in a Military Vehicle

Guillaume Bastard^{1,2}

¹ *Université de Lorraine, Vandœuvre, France*
guillaume.bastard4@etu.univ-lorraine.fr

² *Cassidian Test & Services, Elancourt, France*
guillaume.bastard@cassidian.com

ABSTRACT

This work investigates the field of Integrated Vehicle Health Management (IVHM) and more specifically on the components which are producing or consuming electricity. Firstly, diagnostic and prognostic characteristics are defined. This allows later, from the mapped characteristics, to sort the most relevant methods for critical components. The mapping leads finally to define some scientific issues to be solved in order to improve the diagnostic and prognostic of such components.

1. INTRODUCTION

IVHM is defined by (Jennions, 2011) as “The unified capability of a system of systems to assess current or future state of member system health and integrate that picture of system health within a framework of available resources and operational demand”. One of the purposes of the IVHM is to improve the availability of the vehicle to be able to achieve its mission (Benedettini et al., 2009). It offers online on board processes for components, and integrated processes with tactical and strategic level decision making to get on a dynamic decision of the maintenance based on an assessment of “real” hardware health. In that way, IVHM can provide the critical components, sub-system or system different diagnostic or prognostic processes, alone or combined (Balaban et al., 2010). This proactive consideration is the cornerstone of the Prognostics and Health Management (PHM) philosophy defined (Uckun et al., 2008) as “PHM connects failure mechanisms to system life-cycle management”. To implement this proactive vision, it is necessary to investigate the methods of diagnostics and prognostics suitable to the field of Integrated Vehicle Health Management (IVHM) and more specifically to critical components which are those

producing or consuming electricity (Wilkinson et al., 2004). This state of the art of diagnostic and prognostic methods addresses this problem. According to this context, firstly, the paper defines diagnostic and prognostic processes individually but also coupled to establish a mapping of their characteristics. After the identification of these different characteristics, it focuses on their applications on critical components corresponding to those producing or consuming electrical energy. This allows from the general mapping, to sort the most relevant methods for these critical components. The mapping leads finally to define some scientific issues to be solved in order to improve the diagnostic and prognostic of such components.

2. GLOBAL DIAGNOSTIC AND PROGNOSTIC DEFINITIONS

2.1. Diagnostic

The diagnostic process is generally defined as the actions for the detection, localization, and identification of the cause of failure/breakdown (EN 13306, 2001). (Isermann, 1984) also takes into account the estimation of failure/ breakdown following its identification, to allow the reuse of this estimation in a process of reconfiguration of the system (Zhang & Jiang, 2008).

The diagnostic process has two main characteristics: type of methods and steps of the process. The first characteristic is the type of methods. (Venkat & Raghunathan, 2003) classify fault diagnosis methods into three classes:

- Quantitative model-based methods
- Qualitative model-based methods
- Process history based methods

Another characteristic is the steps of diagnostic process. A decomposition of the process can be found in the ISO 13374-1 (ISO, 2003):

- Data Acquisition
- Data Manipulation
- State Detection

Guillaume Bastard et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

- Health Assessment

In summary the diagnostic process can be defined as the actions for the detection, localization, identification and estimation of the cause of failure/breakdown, characterized by three specific methods and four steps.

2.2. Prognostic

During the last decade, many definitions and methods were proposed in the field of prognostic. (Lebold & Thurston, 2001) define prognostic as “the ability to perform a reliable and sufficiently accurate prediction of the remaining useful life of equipment in service. The primary function of prognostic is to project the current health state of equipment into the future taking into account estimates of future usage profiles”. (Byington et al., 2002) defines prognostic as “the ability to predict the future condition of a machine based on the current diagnostic state of the machinery and its available operating and failure history data.”

The prognostic process has two main characteristics: type of methods and steps of the process. The first characteristic is the type of methods. Generally, prognostics have been classified into three types of methods (Byington et al., 2002) (Jardine et al., 2006) :

- Based on experience / statistic
- Data driven / based on artificial intelligence
- Model based

Another characteristic of prognostic is the steps of prognostic process. (Voisin et al., 2010) have proposed generic prognostic steps:

- To Initialize State and Performances
- To Project
- To Compute RUL (Remaining Useful Life)

In summary the prognostic process can be define as the ability to perform a reliable and sufficiently accurate prediction of the future condition of a system based on his current level of degradation (calculated or from a diagnostic process), projected into the future, characterized by three specific methods and three steps.

2.3. Diagnostic and Prognostic Combination

Diagnostic and Prognostic can be combined in several ways, by coupling methods or by coupling steps at the same hierarchical level of the system, or between two different levels. Further details will be provided later in the document for the combinations highlighted for critical components.

3. METHODS OF DIAGNOSTIC AND PROGNOSTIC IN CASE OF ELECTRICAL ENERGY MANAGEMENT SYSTEMS

To map the previously defined characteristics, the components are separated into several classes, in relation to their functions in an electrical energy management distributed architecture (NATO, 2004) (producer, consumer,

adapter, energy storage) and their technological heterogeneity (electronic, electromechanical, optronic). Each component will be mapped to the characteristic “method” (previously defined) applicable for the diagnostic and prognostic processes. Only methods that can provide fault estimation for the diagnostic process will be mentioned, all other methods can be connected to the survey of (Venkat & Raghunathan, 2003) and provides no added value.

3.1. Energy Producers Components : Rotary Machinery Systems

For diagnostic, quantitative model-based methods are available based primarily on Motor Current Signature Analysis (MCSA) (Haus et al., 2013), on Current Spectrum Analysis (Didier et al., 2007) or on the current amplitude demodulation (Amirat et al., 2010).

For prognostic, (Lee et al., 2014) data driven and model based methods has been applied on rotary machinery systems and he introduces several challenges and scientific issues relatives to this component.

3.2. Energy Adapter Components

For prognostic, (Goodman et al., 2007) defines a method based on the data of the current transformer, his reliability, and monitoring of various energy conversion parameters for power supply. (Impact Technologies, 2011) develops empirical methods based on the physics of components linking the transistor temperature to the Pulse-Width Modulation (PWM) duty cycle, which can be classified into degradation model based prognostic. Also (Balaban et al., 2010) introduces a model based on the physics of transistor, and data obtained from accelerated degradation.

3.3. Energy Storage Components

For diagnostic, a quantitative model based on multi-scale Extended Kalman Filter (EKF) (Hu et al, 2011) could be employed.

For prognostic, data driven methods can be used (Nuhic et al., 2013), or methods based on artificial intelligence using learning algorithms (Chen, 2011). (Pecht, 2011) proposes a physical model based method for Li-Ion batteries.

3.4. Energy Consumer Components : Electronic Controller - Avionic

For diagnostic, (Vichare, 2006) defines several quantitative model based methods for extracting the conditions of use of components from external monitoring (external sensors) or directly from the signals generated by the component.

For prognostic, The most widely used methods in the field of electronics are physics-of-failure (PoF) model based methods that use parameters on the conditions of uses, system life cycle, to identify potential failure and estimate

the Remaining Useful Life (RUL). These methods are being developed on various components, from electronic controllers, to semiconductor microprocessors, via digital electronic components. For example (Impact Technologies, 2011) defines methods applicable to components using Global Positioning System (GPS) or Radio Frequency (RF). (Scanff et al., 2007) presents the results of methods on online replaceable avionic systems, comparing the use of prognosis for maintenance, through experience based methods (used independently of the component), with system life consumption methods (model based).

For combination, (Pecht & Jaai, 2010) defines in his roadmap applied on the development of electronics PHM methods, the possibility of developing hybrid methods (fusion prognostic approach) coupling the benefits of data based methods with model based methods.

3.5. Energy Consumer Components : Electromechanics – Optronics

For diagnostic, quantitative model-based methods of condition monitoring can be applied to the mechanical part (Hameed et al., 2009).

For prognostic (Impact Technologies, 2011) has developed a suite of model based methods for EMA Flight Control Actuators components. (Baysse et al., 2013) also provides model based methods for estimation of the state of an optronic system associated with a decision criterion to allow an adaptation of maintenance policies from the observed state of the system (settling time of the cooling machine).

In summary, for diagnostic, a number of quantitative model-based methods for fault estimation can be used. Only energy adapter components and electronic controller or avionic have a lack of fault estimation methods due to their physical reality, faults are generally abrupt in electronic components. For prognostic, in most referenced work, methods incorporate few data for the step “To Project”: only the current level of degradation is used and the system is covered by a single usage scenario for the projection. For combination few methods are available and the uncertainty is not quantified facing the use of hybrid methods. For all of these cases, component level methods are available, but they are not reused in an energy management system vision.

4. NEW CHALLENGE

The mapping leads finally to define some scientific issues to be solved in order to improve the diagnostic and prognostic of such components for implementing the proactive vision of IVHM:

- For diagnostic, combining diagnostics and prognostics to integrate the two sub-processes together could allow the use of fault estimation of diagnostic in prognostic process by merging “Health Assessment” step in diagnostic with “To Initialize State and Performances” step in prognostic.

- For prognostic, there is a need of contextualization of prognostics based on the operating environment of the vehicle: The methods need to be parameterized in accordance with the contextualization (e.g. mission, conditions, and environment) of the component.
- For combination hybrid approach to diagnostic and/or prognostic need to be explored for coupling the type of methods or step of the process. Uncertainties of these hybrid methods need to be quantified.
- For all of these cases, investigations need to be done to build an energy management system from all of the component methods. This need must necessarily lead us to investigate system level issues. More investigation need to be done for combining diagnostic and prognostic of component-level and provide a system approach focusing more particularly to service oriented vision that need to be rendered to the users by the system functions (to travel, to be protected etc.), as well as his associated targets (environmental impact, travel time etc.).

REFERENCES

- Amirat, Y., Choqueuse, V., & Benbouzid, M. E. H. (2010). Wind turbines condition monitoring and fault diagnosis using generator current amplitude demodulation. In *Energy Conference and Exhibition (EnergyCon), 2010 IEEE International* (pp. 310–315).
- Balaban, E., Narasimhan, S., Daigle, M., Celaya, J., Roychoudhury, I., & Saha, B. (2010). A Mobile Robot Testbed for Prognostics-Enabled Autonomous Decision Making. In *Annual conference of the prognostics and health management society* (pp. 1–16).
- Baysse, C., Bihannic, D., Gegout-petit, A., & Prenat, M. (2013). Maintenance Optimisation of Optronic Equipment. In *Prognostics and System Health Management Conference* (Vol. 33, pp. 709–714). doi:10.3303/CET1333119
- Benedettini, O., Baines, T. S., Lightfoot, H. W., & Greenough, R. M. (2009). State-of-the-art in integrated vehicle health management. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, 223(2), 157–170. doi:10.1243/09544100JAERO446
- Byington, C. S., Roemer, M. J., Kacprzyński, G. J., & Drive, T. P. (2002). Prognostic Enhancements to Diagnostic Systems for Improved Condition-Based Maintenance 1. In *Aerospace Conference Proceedings*.
- Chen, H. (2011). Predicting the Remaining Useful Life of Lithium- ion Batteries with Active Learning and Good- Turing Usage Profile Estimation. In *PHM workshop on battery*.
- Didier, G., Ternisien, E., Caspary, O., & Razik, H. (2007). A New Approach to Detect Broken Rotor Bars in

- Induction Machines by Current Spectrum Analysis. *Mechanical Systems and Signal Processing*, 2007, 21(2), 1127–1142.
- EN. (2001). 13306. *Maintenance Terminology*.
- Goodman, D., Hofmeister, J., & Judkins, J. (2007). Electronic prognostics for switched mode power supplies. *Microelectronics Reliability*, 47(12), 1902–1906. doi:10.1016/j.microrel.2007.02.021
- Hameed, Z., Hong, Y. S., Cho, Y. M., Ahn, S. H., & Song, C. K. (2009). Condition monitoring and fault detection of wind turbines and related algorithms: A review. *Renewable and Sustainable Energy Reviews*, 13(1), 1–39. doi:10.1016/j.rser.2007.05.008
- Haus, S., Mikat, H., Nowara, M., Kandukuri, S. T., Klingauf, U., & Buderath, M. (2013). Fault Detection based on MCSA for a 400Hz Asynchronous Motor for Airborne Applications, 1–19.
- Hu, C., Youn, B. D., Chung, J., & Kim, T. J. (2011). Online Estimation of Lithium - Ion Battery SOC and Capacity with Multiscale Filtering Technique for EVs / HEVs. In *PHM workshop on battery*.
- Impact Technologies. (2011). Avionics and e-PHM Applications Overview. Retrieved from http://www.impact-tek.com/Resources/TechnicalPublicationPDFs/Aerospace/Impact_AAV_AvionicsAndE-PHMAplicationsOverview.pdf
- Isermann, R. (1984). Process Fault Detection Based on Modeling and Estimation Methods A Survey. *Automatica*, 20.
- ISO, I. S. O. (2003). Condition monitoring and diagnostics of machines ISO 13374-1. *Standard*.
- Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510. doi:10.1016/j.ymsp.2005.09.012
- Jennions, I. K. (2011). Integrated Vehicle Health Management Perspectives on an Emerging Field. *Book*.
- Lebold, M., & Thurston, M. (2001). Open standards for condition-based maintenance and prognostic systems. *Maintenance and Reliability Conference (MARCON)*.
- Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42(1-2), 314–334. doi:10.1016/j.ymsp.2013.06.004
- NATO. (2004). All Electric Combat Vehicles (AECV) for Future Applications. *Technical REPORT TR-AVT-047*, 323(July).
- Nuhic, A., Terzimehic, T., Soczka-Guth, T., Buchholz, M., & Dietmayer, K. (2013). Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. *Journal of Power Sources*, 239, 680–688. doi:10.1016/j.jpowsour.2012.11.146
- Pecht, M. (2011). Battery Health and Safety Management. In *PHM workshop on battery*.
- Pecht, M., & Jaai, R. (2010). A prognostics and health management roadmap for information and electronics-rich systems. *Microelectronics Reliability*, 50(3), 317–323. doi:10.1016/j.microrel.2010.01.006
- Scanff, E., Feldman, K. L., Ghelam, S., Sandborn, P., Glade, M., & Foucher, B. (2007). Life cycle cost impact of using prognostic health management (PHM) for helicopter avionics. *Microelectronics Reliability*, 47(12), 1857–1864. doi:10.1016/j.microrel.2007.02.014
- Uckun, S., Goebel, K., & Lucas, P. J. F. (2008). Standardizing research methods for prognostics. *2008 International Conference on Prognostics and Health Management*, 1–10. doi:10.1109/PHM.2008.4711437
- Venkat, V., & Raghunathan, R. (2003). A review of process fault detection and diagnosis Part I: Quantitative model-based methods. *Computers & Chemical Engineering*, 27, 293–311.
- Vichare, N. (2006). Prognostics and health management of electronics by utilizing environmental and usage loads. *Thesis*.
- Voisin, A., Levrat, E., Cochetoux, P., & Iung, B. (2010). Generic prognosis model for proactive maintenance decision support: application to pre-industrial e-maintenance test bed. *Journal of Intelligent* .
- Wilkinson, C., Humphrey, D., Vermeire, B., & Houston, J. (2004). Prognostic and Health Management for Avionics. In *Aerospace Conference, Proceedings IEEE*.
- Zhang, Y., & Jiang, J. (2008). Bibliographical review on reconfigurable fault-tolerant control systems. *Annual Reviews in Control*, 32(2), 229–252. doi:10.1016/j.arcontrol.2008.03.008

BIOGRAPHIES

Guillaume Bastard received the degree of Ingénieur from the Conservatoire National des Arts et Métiers in 2013. He is currently in part time training with the University of Lorraine to receive a M.S in system engineering, diagnostic and prognostic. He works as a Research Scientist at Cassidian Test & Services. His research focus lies in developing and evaluating diagnostic and prognostic methods for engineering systems.