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A Prognostics and Health Management Based Method for Refurbishment Decision Making for Electromechanical Systems

Kai Wang*, Jing Tian, Michael Pecht**, Aidong Xu***

**Lab. of Networked Control Systems, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang, Liaoning 110016*
China (Tel: +8624-23970266; e-mail: wangkai@ sia.cn, xad@sia.cn).
***Center for Advanced Life Cycle Engineering (CALCE), University of Maryland, College Park, MD 20742 USA (e-mail: jingtian@calce.umd.edu, Pecht@calce.umd.edu)*

Abstract: Refurbishing end of life electromechanical products is a value-added operation that provides both economic and environmental benefits. To maximize the benefits from refurbishing, decision making is critical, where the optimized time and the right component for manufacturing are determined. However, there has not been any satisfactory refurbishing decision-making strategy developed. In this paper, a prognostics and health management–based method is developed for refurbishment decision making. First, components are selected for in-situ monitoring using failure modes, mechanisms and effects analysis, then the remaining useful life for the system is estimated by analyzing the in-situ monitoring data so that the optimized refurbishing time can be determined. Finally, near the end of the system life, certain degraded components are selected via diagnosis, and refurbishment is carried out. The procedure of the method is evaluated by an analysis of the refurbishment of instruments in industrial process control. Using this method, the remaining useful life of electromechanical products can be optimally used, and the cost of refurbishment can be minimized.

Keywords: electromechanical system, life extension, prognostics and health management, refurbishment

1. INTRODUCTION

As an electromechanical system nears its end of life, where the system can no longer perform its required functions under the stated conditions, end-of-life decisions should be carried out. One cost-effective approach is to extend the life of the system via refurbishment. Refurbishment is a process that restores the system to satisfy its original specification via procedures like replacing components or modules in the system (Varde et al., 2014). Refurbishment is especially popular for systems where replacement with a new system is not a choice. For example, some systems are too expensive to replace, and some systems have been phased out, so a replacement is not available. Moreover, refurbishment is gaining popularity as it has been identified as a measure to boost productivity, and it has been applied as a marketing strategy (Atasu et al., 2008). Refurbishment also reduces waste and so it is eco-friendly, which results in a reduction of the total life cycle cost of the system. Refurbishment is regularly implemented in a variety of industrial sectors, such as the nuclear industry, the automotive industry, and the electrical and electronics industry.

To perform refurbishment for a system, three questions should be answered. First, is the system worth refurbishing? Second, what is the best time to perform refurbishment? Third, how should the system be refurbished? These questions are critical challenges faced by decision makers. In most cases refurbishment is carried out when a system or its components have failed. The downtime and safety issues resulting from this practice would lead to both economic and safety losses. In some cases, expert experience is used to support refurbishment decision making before actual failure happens. However, expert experience often cannot provide optimal decisions due to the complexity of the degradation process and the operating conditions of the system. For example, the degradation process of an electromechanical system is usually dynamic with intermittent failure and multiple faults. The operating conditions are usually changing, and they may not be monitored. This combination of dynamic processes prevents experts from making an optimal decision based on their experience.

Prognostics and health management (PHM) is a novel approach that can be used to support refurbishment decision making. PHM is an enabling discipline consisting of technologies and methods to assess the reliability of a product in its life cycle conditions to determine the advent of failure and mitigate system risk (Cheng et al., 2010). To determine if a system is worth refurbishing, PHM tools can be used to estimate the life cycle cost associated with the refurbishment of the system. If the cost of refurbishment would be lower than that of a new system, then it would be a cost-effective option. To determine the optimal time to perform refurbishment, PHM extracts a health indicator and estimates the remaining useful life (RUL) for the system based on the indicator. Ideally, the system should be

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refurbished close to the end of its life. To determine how the system should be refurbished, in-situ monitoring of PHM provides diagnosis information so that the degradation levels of critical components are estimated. the components whose degradation levels are above a predefined threshold should be scheduled to be maintained.

In this paper, first, a review of PHM theories and methods is provided. Then a novel PHM-based method for guiding the refurbishment of electromechanical systems is proposed. A System Refurbishing Index (SRI) combined with a component-level health index of each component comprising the system is used in this method to provide effective guidance during the process of refurbishment.The paper is organized as follows. In Section 2 the basic concepts of PHM are described. In Section 3 a novel PHM-based method for guiding the refurbishment of electromechanical systems is proposed. Then an example of applying the method in guiding the refurbishment of instruments in industrial process control is given in Section 4. Section 5 presents the conclusions of the study.

2. PROGNOSTICS AND HEALTH MANAGEMENT

Prognostics and health management (PHM) can support refurbishment decision making through procedures such as system life cycle cost estimation, remaining useful life estimation, and fault diagnosis. PHM has been implemented at different levels of electromechanical systems. From the component level, such as capacitors, to the module level, like insulated gate bipolar transistors (IGBT), to the system level, like complicated circuits. Depending on the approach, PHM can be implemented when a physical model of the failure mechanism of interest can be created, as in the case of electromechanical migration on circuit boards (He et al., 2011), and it can also be implemented when available physics-of-failure models fail to provide satisfactory results, such as in Li-ion batteries and LEDs. In various cases, PHM can be implemented to reduce losses due to reliability issues (Pecht, 2012). An overview of the benefits and challenges of PHM can be found in Sun et al. (2012).

Three approaches from PHM can be implemented in the electronic system life extension in this study. They are the physics of failure (PoF) based approach, the data-driven approach, and the fusion approach.

2.1 Physics of Failure Approach

In the physics of failure (PoF) approach, physical understanding of the system failure mechanism is modeled mathematically to predict the remaining useful life (Pecht et al., 2010). The PoF approach takes both the hardware configurations and the life cycle loading into the failure model. Major inputs with respect to hardware configurations include material properties, geometry, and architecture, while the life cycle loading includes operational loads such as duty cycles and environmental loads such as the environment temperature.

To perform PoF-based PHM, at first a Failure Mode Mechanisms and Effect Analysis (FMMEA) is usually performed to identify critical components that need to be monitored. These components are monitored in-situ, and the in-situ monitoring data are input into the PoF models, which have been developed and validated for the identified critical components, such as Coffin-Manson model that has been used in electronics. Finally, individual component failure models are integrated for the remaining useful life prediction of the systems

In some applications of the PoF approach, a device called a canary, which provides data to generate early warning of functional degradation and impending functional failure, is implemented. Canaries are designed in such a way that they fail early and provide advance warning of incipient failure or information on the degradation trend of the subject electronic component. Canary design requires understanding of material properties and the effects of various operational and environmental loads on ageing of the component.

2.2 Data-driven Approach

In many applications, the failure mechanisms of a component are not well understood, and a PoF model is not available. The data-driven approach is then applied to bridge the gap. In the data-driven approach, data are acquired in-situ using a network of sensors that monitor the system. Features that carry the health information of the system are extracted from the sensor signals through a series of procedures, such as noise reduction, outlier removal, and redundancy reduction. The health states of the system are then estimated based on the extracted features via methods for decision making, such as machine learning techniques. Based on the use of historic data, machine learning techniques can be classified as supervised learning techniques and unsupervised learning techniques.

In supervised learning, historic data are used to train an algorithm to establish regions of different health states of the system. The current health state of the system is determined by classifying the current data to one of the regions. Widely supervised learning techniques include Support Vector Machines, (SVMs), Artificial Neural Network, and Fuzzy-Artificial Neural Networks (Oukaour et al. 2011).

Unsupervised learning techniques do not need data to train any algorithm. The data are partitioned into different clusters, and the health state of the system is determined by examining characteristics of the clusters. Widely used unsupervised learning techniques include k-means clustering and the Gaussian mixture model. To predict the future health state, or the remaining useful life of the system, prediction tools such as Bayesian Network, Particle Filter (Xing et al., 2013), and Kalman Filter (Fan et al., 2013) are used. In addition to machine learning techniques, statistical techniques such as the sequential probability ratio technique (SPRT) and Markov Chains have also been used to estimate the health state of the system.