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

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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.

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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...
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 (FMEA) 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.
When complex systems, the data-driven approach is an effective approach for implementation of the PHM system, as in case of laptop computer battery state of charge and state of health estimation, and in the application of more complicated systems such as the Joint Strike Fighter (JSF) Program.

2.3 Fusion Approach

Both the PoF approach and the data-driven approach have some advantages and limitations. To overcome the limitations, a fusion-based approach for prognostics was developed. In the fusion-based approach, the PoF and data-driven approaches are used to complement each other to meet the end goal of life prediction for electronics.

The first step in the fusion approach is to identify the precursor for implementing the PHM. The next step is to identify the sensors or sensor mechanisms to track these precursor parameters. The sensor data acquired online are utilized for evaluation of any deviation from the reference or healthy condition of the system. This is performed by extracting the characteristic features from the sensor data and comparing them with the baseline data. If any deviation exceeds the pre-set limit, an alarm is generated and provides an early warning signal for the incipient failure. The PoF module takes this in-situ monitored data to update the PoF model of the system and provide the estimates of remaining useful life. These new data become part of the historical database and are utilized for further fine-tuning of the prediction capability of the fusion model.

A fusion approach has been implemented for railway health assessment (Galar et al., 2013). The advantage of fusion approach was demonstrated by an application to the remaining life prediction of an aircraft gas turbine engine. Electronic systems under extensive research include lithium-ion batteries and LEDs due to their complexity in life assessment. To estimate the state of charge (SOC) for lithium-ion batteries, a physics-based simulation model of the battery was developed, while the model parameters were tailored online by employing a data-based Kalman filtering technique to estimate the SOC. In LED life assessment, conventional methods are based on extrapolation of the data and curve fitting to predict the future state of lighting. These methods do not take into account chromatic state shift as an input for prediction. Using the fusion approach, an unscented Kalman filter was used to track the future chromaticity state, where the accuracy of prognosis was improved (Fan et al., 2013).

3. A NOVEL PHM-BASED METHOD FOR REFRUBISHMENT DECISION MAKING OF ELECTROMECHANICAL SYSTEMS

The framework of the method proposed is shown in Fig. 1. First, the system to be refurbished is divided into several components according to the characteristics of each component. Then the potential failure mechanisms of each component are identified by FMMEA and the related failure history reports of the system. Next, a PHM method is developed to evaluate the reliability of each component in its actual life cycle environment and operating loads according to the characteristics of failure modes of each component when the system is running. According to the characteristics of different types of components, either the PoF, data-driven, or fusion method mentioned in Section 2 can be used. Considering that different types of components have different failure mechanisms, for example, electrical and mechanical components have different failure modes and are affected by different environmental and operating loads. Therefore, the proper strategies for fault detection and diagnosis have to be determined according to the characteristics of the corresponding component so that the component-level Health Index (HI), which is a quantitative index to assess the component health status, can be obtained for each component. Then SRI is calculated based on these component-level HIs and the corresponding component weight information, which can be obtained by system architecture and component importance analysis. Finally, the SRI, combined with the component-level HI for each component, can be used to make remanufacturing decisions, such as when the best time to start remanufacturing, which components need to be refurbished, and so on.

![Fig. 1. The framework of the PHM-based method for refurbishment decision making of electromechanical systems.](image)

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Considering that the PHM method is performed when the system is running, this method contributes to ensuring system safety and minimizing the maintenance cost during refurbishment.

4. CASE STUDY

As is commonly known, instrumentation (process connections, instruments, wire, conduit, logic solver, control programming) makes up the brain and central nervous system
of a process operation. These pieces of equipment, when healthy, ensure safe and reliable operation, product quality, customer satisfaction, and optimal production capability (Skweres, 2011). Therefore, the time to perform refurbishing and how to refurbish instrumentation play a decisive role in the safety and economy of the plant. In this section, the method proposed is applied to guide the refurbishment of a smart pressure transmitter (PT), which is one of the most important components involved in process instrumentation.

4.1 The Architecture of the smart PT

A smart PT is a classical electromechanical system that is designed to measure pressure and differential pressure (including level and flow). The architecture of the classical PT used in a nuclear power plant is illustrated in Fig. 2. It is composed of the following three components: sensing lines, the sensing element, and electronics. Sensing lines are used to connect the pressure transmitter to the process piping, reactor vessel, or primary flow elements, in order to transport a pneumatic or hydraulic signal from the process to a transmitter. Then the sensing element transfer the pneumatic or hydraulic signal received to the electrical signal which can be processed by the electronics. Finally, the electronics transfer the signal in its proper form to other instrumentation and the control room to implement the control function.

![Fig.2. The architecture of a classical smart PT system.](image)

4.2 Component classification and FMMEA analysis

According to the architecture of the smart PT, the following three components will be considered in this paper: the sensing line, the sensor, and the electronics. The failure modes of each component can be identified by the related reliability database, such as the Licensee Event Report (LER) database (NRC, 2014), the OREDA database (SINTEF, 2009), and so on. The main failure modes for each component are described as follows.

- Failure mode for the sensing line

The sensing line is mainly affected by the mechanical stress. According to the LER database, nuclear power plants have encountered many events involving blockages, voids, and leaks in pressure sensing lines, which will increase the response time of the PT. Therefore, detecting the health status of a sensing line and taking the corresponding maintenance actions are very important during refurbishment of the pressure transmitters in nuclear plants.

- Failure mode of sensor

The steady-state performance of the sensor in the process instruments will change because of changes in temperature caused by body heat, handling, etc., which will lead to drifts in the sensor. The bias in the sensor is the main failure mode for the sensor, which will be discussed in this paper. Experiments show that the response time of the PT will increase when the sensor drifts.

- Failure mode of electronics

The electronics consists of a circuit board, electrical elements, and so on. For illustration, only the interconnection/solder joint failure of the circuit board, which was identified as the dominant failure mechanism (Vichare, 2006) for the circuit board, is considered in this paper. Other failure modes can be dealt with similarly.

4.3 Component-level HI calculation

Proper fault detection and diagnosis methods have been proposed according to the characteristics of the failure mode of each component to calculate HI. Here the allowable values of HI are decimal numbers from 0.0 to 1.0. Two extreme situations are as follows. If the component functions as specified and do not degrade at all, its HI value is specified as 1.0; otherwise, if the component failed to function completely, their HI value is specified as 0.0.

- Sensing line HI calculation

The sensor output signal is composed of the static and dynamic components. The dynamic signal, namely the noise signal, can be used to detect sensing line blockage (Hashemian, 2011). A noise analysis–based method for calculating the sensing line health index is shown in Fig. 3. The features of the noise signals are first extracted by the Fast Fourier Transform (FFT) to obtain its power spectral density (PSD), which is then used to calculate the PT’s response time (RT). The sensing line HI is then obtained by comparing the extent of increase with the baseline RT value.

![Fig.3. The principle for calculating the sensing line health index.](image)
The static signal in the sensor output is used to detect drift Multivariate State Estimation Technique (MSET). The basic process for calculating HI is shown in Fig. 4. Firstly, training sample data are used to construct a mathematical module of the sensor. Then the actual output of the sensor is compared to the expected output by the mathematical model to produce the residual, namely the drift. Then the drift is converted to the RT through the Drift-RT relationship model, and finally the HI can be calculated by assessing the extent of increase of RT.

\[ SRI = \sum_{i=1}^{N} w_i x_i \]  

(1)

where,

- SRI is the system health index,
- \( N \) is the number of the components in the system,
- \( i \) represents the \( i \)th component in the system,
- \( x_i \) is the component-level HI of the \( i \)th component,
- \( w_i \) is the weight of the \( i \)th component. Its range is between 0 and 1 and the sum of \( w_i \) (\( i \) from 1 to \( N \)) is 1. This value can be obtained by considering the system architecture, the function that the component performs, the refurbishing cost factor of the component, and so on.

Since SRI can be calculated in real-time, the time-SRI curve can be plotted and the expected results are shown in Fig. 6. As shown in Fig. 6, the SRI value decreases as the time increases. In particular, a threshold interval, namely between \( t_{\text{threshold1}} \) and \( t_{\text{threshold2}} \), is determined by system safety requirements, benefit factor, lead time of spare components, and so on. When the value of SRI locates in the interval, it is the best time for refurbishment. If the time for refurbishment is earlier than \( t_{\text{threshold1}} \), it is not a cost-efficient solution. Otherwise, if the time is later than \( t_{\text{threshold2}} \), the system will face high risk for suffering accidents. Further, the refurbishment decision making can be accomplished by combining the time-SRI relationship curve with the component-level HIs.
A novel PHM-based method is proposed in this paper for refurbishment decision making for electromechanical systems. A SRI combined with component-level HIs were used to determine the optimized time and the right components for refurbishment. The remaining useful life of electromechanical products can be optimally used, and the cost on refurbishing can be minimized by using this method. The work in the future is to perform sensitivity analysis of the related metrics calculated for the refurbishment decision making procedure to determine their range and corresponding uncertainties.

5. CONCLUSIONS

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