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Christian Berenger WANDJI WOUAPI, Helmi Ben Rejeb, Peggy Zwolinski

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Characterization of the state of health of a complex system at the end of use

Christian Wandji[a]*, Helmi Ben Rejeb[a] , Peggy Zwolinski[a]

[a]Univ. Grenoble Alpes, CNRS, Grenoble INP,G-SCOP, 46 Avenue Félix Viallet, 38000 Grenoble, France

* Corresponding author. Tel.: +33 4 76 57 48 44, E-mail address: christian.wandji-wouapi@grenoble-inp.fr

Abstract

The state of health (SoH) of an end-of-life product is one of the levers for optimizing the circular economy (CE) process in order to allow the product life-extension. Many approaches have been developed in the literature to estimate the SoH of a complex system (CS). In this study, we asked ourselves the following two questions: First, how to optimize the circular lifecycle scenarios of the components of a product at its end of life? And second, how to estimate the SoH of a product at the end of its life? To answer these questions, we proceeded as follows. First of all, the state of health of a product needs to be considered as an important parameter as well as performance or reliability. To estimate the SoH, it is necessary to identify the product parameters to be observed. The problem here is to choose the most relevant parameters among all those available for a CS. To do this, we have proposed a conditional-based maintenance approach (CBM) which consists in establishing the fault tree of a product. It consists of functionally breaking down a product into its various components and identifying the main failures for each of them. Then, these failures are used to identify the parameters to be monitored. Second, based on the most relevant parameters, the health indicators needed to estimate the SoH of the product are obtained. Then, the Prognostic and Health Management approach (PHM) is proposed in order to estimate the SoH. In the objective of providing a general solution that could be used for estimating the health status of any product, we have proposed a generic framework for the PHM approach. It serves as a guide in choosing the right approach according to the situation. Then, we proposed a decision-making strategy to optimize the process of orienting components in circular loops. This strategy is based only on the technical-functional indicator, which is the SoH of the components. Finally, we showed an example of the implementation of the proposed method for the case of the electrical scooter motor.

Keywords: Health indicator; Sate of health ; circular economy; lifecycle engineering, condition-based maintenance; Prognostic and Health Management.

1. Introduction

Having become aware of the real danger that threatens our environment, manufacturers and scientists use several concepts, such as sustainable development, circular economy, to minimize energy waste and pollution and optimize the use of resources. Within this framework, the project Smart 2020 entitled: “Collaborative construction of the state of health of a product to be regenerated throughout the lifecycle” has been launched and supported by the French network S.mart. This latter federates an academic community to drive scientific, technological and societal change at local and national levels for the industry of the future. The study presented in this article tackles the issue of optimization of the circular scenarios of end-of-life (EoL) products. The CE is one of the most important concepts that really impacts the resources management. It is made up of many processes that allow to recapture the added value of the product at different levels of the value chain, the user, the service provider, the product manufacturer, and the component manufacturer. Those processes are reuse, repair, repurposing, refurbishment, remanufacturing, and recycling and then constitute a close loop system [1]. They are widely discussed in the literature but the question on the optimization of their use is not yet clear. In other words, how to direct the components of a complex system (CS) towards the appropriate CE processes in order to reduce

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waste and recapture the value-added of the components as much as possible? To do this, the knowledge of the state of health (SoH) of these components is paramount. Therefore, the question of the ways to assess the health state of the components of a CS deserves a particular attention. In this paper, CS is defined as a system made up of several subsystems or components from different fields (mechanical, electronic, electrical, among others) [2]. The SoH is more related to the state of degradation that has widely been assessed in the literature using the prognostic and health management approach (PHM) [3], [4]. Therefore, PHM is most effective when applied to critical components. Therefore, it is necessary to identify them first. Thus, we have proposed a condition-based maintenance (CBM) method that is compatible with PHM in the case of a combination of both approaches [5].

The remainder of the paper is organized as follows: section 2 summarizes the methodology proposed to presents the research questions. The literature review is presented in section 3. The development of our general framework, in which CBM approach, PHM approach, and the decision-making strategy were presented, is discussed in Section 4. The section 5 presents an illustration of the implementation of the proposed method on an electrical scooter motor. Finally, the conclusion is given in section 6.

Nomenclature

CBM	Condition-Based Maintenance
CE	Circular Economy
CS	Complex System
EMD	Empirical Mode Decomposition
EoL	End of Life
EV	Electric Vehicle
FA	Functional Analysis
FMEA	Failure Modes and Effects Analysis
FMMEA	Failure Modes, Mechanisms and Effects Analysis
GRNN	Generalized Regression Neural Network
HHT	Hilbert-Huang Transform
HI	Health Indicator
LIB	Lithium-Ion Battery
LRT	Linear Rectification Technique
ML	Machine Learning
PDF	Probability Density Function
PHM	Prognostic and Health Management
PLM	Product Lifecycle Management
PoF	Physic of Failure
RCM	Reliability-Centred Maintenance
RFID	Radio Frequency Identification
RMS	Root Mean Square
RUL	Remaining Useful Life
S.mart	Systems Manufacturing Academics Resources Technologies
SoH	State of Health

2. Research methodology

The objective of this paper is to estimate the SoH of a CS in order to optimize the process of directing components towards CE scenarios. To achieve this goal, we proposed a method that could be considered as a general framework for SoH estimation and decision-making method towards implementation of CE scenario. The method needs to be versatile and robust enough to cope with different situations, whether operating history data are available or not. It combines several methods from the areas of reliability engineering, data science and artificial intelligence. The general research methodology that we have used in order to construct this framework consists of the following two steps. First, a comprehensive and systematic literature review has been carried out. It is through bibliographic research that we have traced the path of methods used for failure detection, diagnosis, and prognosis. Second, a 3-step framework is proposed, which aims at the identification of critical component, SoH estimation, and decision support for circular scenarios. We have proposed the CBM approach to identify critical components of the system and their main failures. Then, the PHM approach which on the basis of these failures will select the important parameters from which the Health Indicators (HI) will be extracted for the SoH estimation. Finally, the SoH ranging from 0 to 1 is estimated for each component, and it is used with a decision-making strategy to direct the components to one of the following circular processes: reuse, repair, repurpose, remanufacture, refurbish, and recycle. This decision-making strategy only considers the technical functioning indicators expressed in terms of SoH, but it could also consider other indicators such as economy, ecology, business, market.

3. Literature review

The SoH concept comes originally from medicine and was used to characterize human health. Since then, it has been used to characterize the health of systems. The question of the SoH of an item of a piece of equipment arose in reliability engineering, because one of the missions of maintenance on a technical level is to increase the lifespan of the equipment. Thus, the concept of maintenance was concerned first with promoting repair of a piece of equipment at each failure, then it promoted the systematic or conditional change of the components before the failure occurs [6]. Indeed, from the systematic maintenance, the follow-up of the state of degradation was introduced. Zhang et al. [7] proposed a solution to estimate the remaining useful life of a system with high fluctuating degradation. They proposed to use degradation process and standard deviation as performance variable to calculate the Probability Density Function (PDF) and then the conditional reliability function which is the estimation of the RUL. The purpose of the reliability calculation is to increase productivity, so it concerns much more the equipment available in a factory where the environment and the conditions of use are known. So, what about the reliability calculation of a product that operates in an unknown environment, or a product used by a third party, for which a regular follow-up is not possible.

To address those questions, Morello et al. [8] proposed to use Product Lifecycle Management (PLM) to track the status of a smart product during its whole life cycle. This consists in recording the operating information of an intelligent product in the memory of an RFID card installed on it. This method is extremely useful on a simple system like the example of the hydraulic cylinder that Morello shown in his article. But it could become much less efficient or terribly expensive in the case of a CS. However, following a demand from industry for greater reliability with lower cost, the PHM approach has emerged in recent years as an essential solution for estimating the RUL as presented by Kalgren et al. [6]. PHM is the most suitable approach for predicting the RUL of a CS because it incorporates the principles of CBM as well as those of Reliability-Centered Maintenance (RCM) [9], [10]. It can be classified into three types: model-based, data-driven and hybrid approach [2], [11].

A model-based approach consists of mathematically model the physical degradation of a product. It gives most accuracy than the others approach. But because of costly and the difficulty of implementation on a system with several subsystems and components, it has low applications in real life [12]. On the other hand, model-based approach is suitable for new products because it reduces the design margin [8]. However, because of the complexity of this approach, it is not enough employed by researchers compared to data-driven approach.

The data driven approach is useful when the product has already been manufactured. It traditionally consists of analyzing online and offline data to provide degradation behavior, then constructing a HI using different methods to finally predict RUL using a trained data model. There are many models of data to predict RUL and the most used are those of Machine Learning (ML). Compared to the model-based approach, data driven approach has many applications. For Lithium-ion battery [14], [15], turbofan [4], [16], bearing [3], [17], [18] and others. To avoid the shortcomings associated with the use of one of the above approaches, some researchers have used hybrid approach (i.e., a combination of two or more approaches).

One most used hybrid approach is the combination with model-based approach and data-driven approach. This approach is recently used to estimate the SoH of lithium-ion batteries in real time without RUL prediction. It takes advantage of the data-driven least squares support vector machine and the model-based unscented particulate filter shown by Song et al. [19]. On the other hand, still for Li-Ion batteries, Su et al. [20] proposed a hybrid PHM approach to estimate the remaining capacity using a generalized regression neural network (GRNN).

Our literature review determine that the main purpose of estimating the RUL through the PHM is to optimize the maintenance actions. However, in the application of the PHM there is always a final decision-making step. Very few studies used PHM to estimate the SoH of a product for decision making in the context of the CE. In this perspective, some publications on decision-making strategies have been identified. This is the case of Alamerew et al. [21], [22] who proposed many decision-making strategies regarding different criteria in the context of circularity. Those criteria are mainly environmental (EoL impact indicator, CO2 emissions, SO2 emissions, energy consumption, among others), economic (such as logistic cost, product cost, disassembly cost) and societal (such as number of created employees, exposure to hazardous materials). But it is also possible to consider other criteria such as legislation, business, market and technical. It is also the case of Anityasari et al. [23] who proposed a decision-making tool to direct components at the end of their life toward reuse, remanufacturing, and recycling process on the basic of profit margin, market price, product life cycle cost, cost of remanufacturing, and cost of warranty.

4. General framework

Our work aims to fill a gap in the literature by proposing an approach for estimating the SoH of a product in order to optimize the choice of circular scenarios for the products EoL. To achieve this goal, we propose to combine CBM approach, PHM approach and a decision-making method as it is illustrated in Fig. 1.

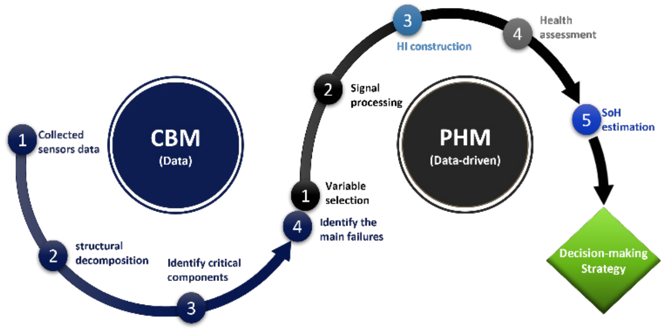

Fig. 1. General framework

On the one hand, PHM approach has been selected because it incorporates the principles of CBM as well as those of RCM, and it is recommended for RUL prediction using health assessment. It is made of several steps that start with the selection of relevant variables related to components. Then, the data is processed, and the HI is extracted to monitor the degradation of the component. Finally, the SoH is evaluated and can be estimated. However, it is recommended to use the PHM for the most critical components, as they best describe the degradation of the system. Hence, it is combined with the CBM approach. On the other hand, the CBM approach is used for data or information collection, detection and diagnosis of the main critical component and the main failures of each critical component. It uses detection and diagnostics to monitor a CS with the aim of identifying degradation status, faults, their severity, and their causes [5]. CBM and PHM are followed by the decision-making step of the framework, which used the SoH value to direct the CS components to the appropriate CE scenarios.

4.1. Condition-based maintenance approach

CBM methodology consists of monitoring the state of degradation of an item of a piece of equipment and then triggering maintenance actions each time the predefined thresholds are exceeded on the basis of several significant criteria [13]. In our proposition, we used the CBM approach to identify the critical components of a CS and their main failure. Thus, we proposed a process made up of a set of maintenance analysis tools such as Failure Mode and Effects Analysis (FMEA), Functional Analysis (FA), Pareto chart and Fault Tree method.

The process presents two possibilities to establish the fault tree of a CS. One possibility is to make a FA of the CS in order to obtain its hierarchical structural decomposition into its components. Then, Pareto chart on the number of downtime (N) of each CS component allows the identification of its critical components. Indeed, this possibility of using the FA and Pareto chart tools is only possible if the operating data of the system are available and the information on the system such as its structure is known. Otherwise, the second possibility consisting of making a FMEA analysis on the CS. FMEA allows to highlight the potential critical part of the system, their main degradation modes and failures and their criticism. Thus, the criticism is calculated on the basis of the manufacturer's technical documentation (TD), as well as the experience and expertise of the engineers in charge. FMEA is most useful tool when the system is unknown, and the data are not available.

Finally, whatever the path taken, the final result is to build a fault tree that will show the critical components and their main failure identified using the above-mentioned tools. So, knowing the main failure of critical components, we can monitor the variables that best characterize the degradation of the system. They will be the inputs of the next approach, which is PHM.

4.2. Prognostic and Health Management (PHM)

This section aims at estimating the SoH of each identified critical components from the CBM approach, as explained above. PHM approach is therefore classified into three types, model-based, data-driven and hybrid approach. Depending on the type of system (i.e., complex, or simple), the ability to model degradation, type of degradation (i.e., progressive, or sudden), acceptable uncertainties and available data, the selection of the appropriate PHM approach has been proposed. Indeed, depending on the failure of the critical component from the CBM approach, the choice of the appropriate PHM approach is required.

The model-based approach is chosen when the degradation of a component can be physically modeled. Better known as Physics of Failure (PoF), it is an approach based on modelling the physical degradation of the system [13]. It is mainly based on the experience and knowledge of experts. It uses product lifecycle load conditions, failure modes, failure mechanisms and some product information (such as composition, material properties, relationships between components) to assess the reliability of the product [11]. Its implementation can be based on Failure Modes, Mechanisms and Effects Analysis (FMMEA), as it is used to identify potential failure modes and high priority failure mechanisms, in addition to determining the causes and effects of failures as FMEA does. Within this perspective, the PoF implementation approach developed here is based on FMMEA. Then, based on certain information on the CS like its compositions, properties, lifecycle load conditions and experts advices, a FMMEA table is constructed as the example shown on Table 1 [24], [25].

It also provides the relevant parameters (loads) that need to be monitored. For example, in the FMMEA example in Table 1, the relevant load for the pump controller is temperature. For each load of each component, a physical model is selected to calculate the damage and then estimate the SoH. Still in FMMEA example, the physical model that could be applied for the pump controller case is the nonlinear or power law model (Coffin - Manson).

Table 1. Example of FMMEA table for a fuel delivery system [24]

Components	Function	Fault	Causes	Mechanism
Pump controller	Regulate signal	Short circuit	High temperature	Thermal degradation
Fuel Tank	Provide Liquid	Partial crack	Contamination	Corrosion

Unlike the model-based approach, the data-driven approach is recommended when the degradation of a component cannot be physically modeled. It can only be used if historical sensor operating data are available. Data-driven approach mainly consists in training a model on data with ML methods in order to predict the degradation behavior of the system in the near future before the failure occurs.

The application of the data-driven approach is based on the use of history HI data. These data are divided into two main types: on the one hand, the variables, which represent the records of the sensor signal, and on the other hand, the target, which is what we want to estimate. In this paper, the target is the SoH levels for different CE scenarios.

There are several steps to implementing the data-driven approach. Then, the first step consists to identify the most relevant variables. This variable selection step could rely on the result of the fault tree carried out in the CBM approach and which provides the failures and their causes for each component. Thus, the parameters that can measure the cause of the failure could be the relevant variables. Nevertheless, it is recommended to use other methods such as particle filter algorithm, wrapper selection to find the correlation between these variables and the target. The second step is about performed the signal processing in order to get residual reliable signal using data analysis methods such as using Empirical Mode Decomposition (EMD) [3], Fourier method or Linear Rectification Technique (LRT) [18]. Then, features or HIs are extracted in the third step from the relevant variables (those that best describe the system degradation). Many methods have already been used, such as the Root Mean Square (RMS) used by Ahmad et al. [18], or Hilbert Huang Transform (HHT) used by Soualhi et al. [3]. In the case of this paper, four HIs were considered, namely the slope, the intercept of the curve fit, the mean, and the variance. They have already been used by Mosallam et al. [4] to estimate the RUL of a lithium-ion battery (LIB) and a turbofan engine. In addition, these HIs can be extracted from any existing signal. That is why they are proposed here. Then, the next step is to train many ML models in order to keep the one with the best score or the minimum error. A ML model is an algorithm that learns the degradation behavior of a system from history HI data and predicts the future behavior of the same system with the current real-time HI data. Finally, the processing of online and real-time data is similar the one of offline data, it consists of three steps (variables selection, then signal processing and then HI extraction) and uses pretty much the same methods. A selected model is trained with the historical HI data and then it is used on the online data to estimate the component SoH.

However, data-driven approach is data-depending and because of that, it could be limited with the lack of data or the lack of reliable data. And it is less accurate than the model-based approach. That is why model-based approach is most recommended for the RUL estimation. But its implementation remains complex and costly. Even more so in the case of a CS, it might be extremely complicated, if not impossible, to model the physical degradation of system. To overcome the gaps related to the application of one of the two previous approaches alone, we have proposed to use the two approaches in a complementary. It means, record data of the components we have to apply data-driven approach and model the physical degradation of those for which we cannot obtain data using model-based approach. Thus, we recommend using a data-driven approach for critical components for which we have sensor data and using a model-based approach for others.

4.3. Decision-making strategy

The main objective is to optimize the CE scenario of the components based on the knowledge of their SoH, keeping as much value as possible in the manufactured product. In fact, if the SoH estimation gives a result between 0.8 and 1, it means that the component is still healthy, and that it is in the mature phase of its life. It can therefore be repaired or reused in case of failure. But, if the SoH is between 0.6 and 0.8, three scenarios are possible. The first is that the component is reassigned if it can be used for another application. This is the case for example of LIB battery for electric vehicles (EV). When its capacity reaches 80%, it can be repurposed in less demanding application (energy storage or less power-intensive mobility applications). Of course, if the capacity alone reflects the SoH of the LIB. The second scenario is remanufacturing or refurbishing if the component in question is re-manufacturable. But if the component is not reusable, it is recyclable. Or in the worst case, the component is thrown away.

This decision strategy is based on only one indicator, the SoH of the component. But it could take into account other indicators such as environmental (environmental impact assessment), economic (cost price), social (job creation potential), marketing (market needs). But also, the legislation, the companies, the market.

5. Illustrative case

In this section, the implementation of the general framework is showed for the case of an electric scooter motor. This application is part of Smart 2020 project and relies on the Progress 4.0 platform of the University of Lorraine, which studies the challenges raised by Industry 4.0 concept. The objective of this platform is to disassemble the product to the optimal level of decomposition. This optimization of the decomposition level is defined according to the SoH of the product to be regenerated. The principle is then to estimate the SoH of the product and to make a decision on its future. It is either stored because it has a good SoH, or disassembled into different components. Then, the SoH of each of its components is estimated before a decision is finally made.

Thus, to evaluate the SoH, the method proposed in this paper was used. Because of the unavailability of engine operation data, the FMEA tool was used to identify the main failures and their causes. Then, the PHM approach was applied to the whole engine and depending on the result, the engine must be either decomposed to evaluate the SoH of its components, or simply stored. Since the data is missing, the PoF-based PHM approach can be applied, which requires the integration of experts. Its application consists of identifying potential failure modes and high priority failure mechanisms, namely power degradation in the case of the engine. Then, the relevant parameters, called health indicators, related to this power degradation are determined. Finally, the appropriate analytical model for estimating the SoH is selected. However, this model needs the vibration sensor data as the relevant parameters. Finally, the vibration sensor data must be recorded in order to evaluate the SoH result with the chosen Basquin model according to the experts. During these tasks, experts in the engine field are integrated in order to provide their experience and knowledge about the identification of relevant health indicator and model for estimation of SoH.

6. Conclusion

The method proposed in this paper is a solution to optimize the process of orienting the components of a complex system to the appropriate CE scenario while keeping the maximum value put into the manufactured product. Thus, this proposal is a set of three approaches, the CBM that allows to identify the critical components of a complex system, the PHM that allows to estimate the SoH of these components and a decision support strategy for the orientation of these components to the CE scenarios. The added value of this work will be the time saving in the orientation towards the circular economy processes, the conservation of the maximum value put into the manufactured products and an optimization of the design stage, because in this case, for instance it will be possible to design with the aim of being able to remanufacture a component of a product after a certain threshold of use. Moreover, it can be combined with several tools of the industry 4.0 concept like IoT, Big data for better monitoring and prognostic performance. Finally, this work presents points that could be deepened such as the question on the reliability of the data recorded by the sensors, the methodology of choosing the appropriate machine learning model for the data collected in the framework of the data-based approach. Another perspective to this work is conduct a study on a product with the use of operating data of its different parts enabling to determine the SoH of its components. This could be an opportunity to fully test the decision method approach proposed and bring constructive methodological and practical insights about its use within the implementation of circular economy scenarios.

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