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ORIGINAL ARTICLE

# Degradation mode and criticality analysis based on product usage data

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**Abstract** Over the last decade, a rapid development of internet, wireless mobile telecommunication, and product identification technologies make whole product life cycle visible and controllable, which can improve several operational issues over the whole product life cycle: product design improvement, predictive maintenance, rational decision on end-of-life products, and so on. The key element to solve these issues is to assess the degradation status of a product based on gathered data during product usage period. However, despite its importance, due to the interrupted information flow of the product life cycle after product sales, it has not received enough attention in the literature until now. To overcome this limitation, this study develops a decision support method, called degradation mode and criticality analysis (DMCA), for the analysis of product degradation status based on gathered product usage data. The proposed method enables us to identify and assess the degradation status of a product and give a suitable guide for the next action. To show the effectiveness of the proposed approach, a case study for a heavy construction equipment vehicle is introduced.

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## 1 Introduction

In general, at the beginning of life (BOL) phase which includes product development and production processes, the information flow is connected thanks to several information systems such as computer-aided design and manufacturing (CAD/CAM), product data management (PDM), knowledge management (KM), enterprise resource planning (ERP) systems, and manufacturing execution system (MES). However, the information flow of middle of life (MOL) and end of life (EOL) including usage, maintenance, service, reuse, recycle, and remanufacturing processes is often disconnected so that the management of product life cycle information after BOL phase is difficult. For instance, in the case of consumer products such as consumer electronics, household machines, and vehicles, the flow on product information is disconnected after the delivery of a product to a customer [1]. More and more information is disappearing as product passes through its life cycle from production, to retail, to consumers, to disposal, remanufacturing, or resale [2]. Only a few methods such as consumers' survey and after-sales supporting systems are able to restrictively collect product information during MOL and EOL phases. Because of this disconnection, the visibility of product information generated within MOL and EOL phases is often limited.

Collecting product information during MOL and EOL phases makes a product itself or product operations improved in a various way, e.g., by the improvement of design or the optimization of maintenance operations. Since a critical failure or degradation of a product during its operation can seriously damage the belief of customers on the product reliability, the design improvement or maintenance enhancement for preventing the critical failure or degradation in advance has precedence over any other things in a company. Recently, owing to emerging product identification and sensor technologies, it becomes possible to collect product information from MOL and EOL. Lots of manufacturing companies are trying to adopt new technologies and get more accurate real-time information regarding product status during its usage period. As the available information becomes diverse, the new opportunity to use them for preventing a critical failure or degradation in advance becomes increasing.

However, there has been a lack of methods to combine product usage information with design improvement and maintenance in a systematic way. Although there have been some related research works, there is still the limitation in the decision framework or guidance for assessing product status based on gathered product usage data. Due to this limitation, the design improvement and maintenance operations have been done based on incomplete information, which leads to the increase of design and maintenance costs. Hence, it is necessary to develop a decision support method applying product usage data into supporting design improvement and maintenance enhancement.

To this end, this study deals with the development of a decision support method, called degradation modes and criticality analysis (DMCA), which identifies the degradation of product status and its criticality based on product usage data. As product operation time increases, the product performance usually decreases, and this phenomenon is defined as degradation. The more degradation in product operation than expected in product design gives rise to undesirable problems during product operation. Hence, it is necessary to manage and control degradation for giving better reliability to customers. Recently, some research projects have applied emerging product identification and sensor technologies, e.g., product embedded information devices (PEIDs) of EU PROMISE project [1], to gather and analyze product degradation status into their case studies. This study is based on one application of EU PROMISE project that proposes a systematic method to use MOL data for design improvement and maintenance enhancement (see Fig. 1). By understanding product degradation behaviors, product design and maintenance operation can be improved since the product failure is closely related with the product degradation behavior. Middendorf et al. [3] stressed the importance of information related to product degradation for sound strategies of product design, market research, quality management, maintenance, reuse of components, or recycling. To get the useful information related to product degradation, how to assess the product degradation from gathered product status data and how to analyze its effect on the product failure should be clarified and specified. To this end, the DMCA method is developed in this study.

The remaining of this study is organized as follows: Sect. 2 introduces relevant previous research works. Section 3 describes the DMCA method in a stepwise manner. Finally, Sect. 4 introduces a case study that applies the proposed approach into a heavy construction equipment vehicle.

## 2 Previous research

In general, degradation is a phenomenon where certain measurements of quality characteristics deteriorate over time [4]. The exact understanding of the degradation is prerequisite to understand product operations and to improve the product. The degradation can occur when a product or its components and parts lose functional abilities due to various reasons such as wear, corrosion, and vibration. The performance degradation indicates how much the functional ability is hampered compared to design specification. Since the ability to achieve the functional objective is impaired as time goes by, the performance degradation usually increases.

There have been various efforts to analyze the degradation of product status and use its result effectively. The statistical behavior of degradation data and its related applications have been well studied in the previous literature [4]. For example, Lu et al. [5] proposed a degradation model to compare degradation analysis and traditional failure-time analysis in terms of

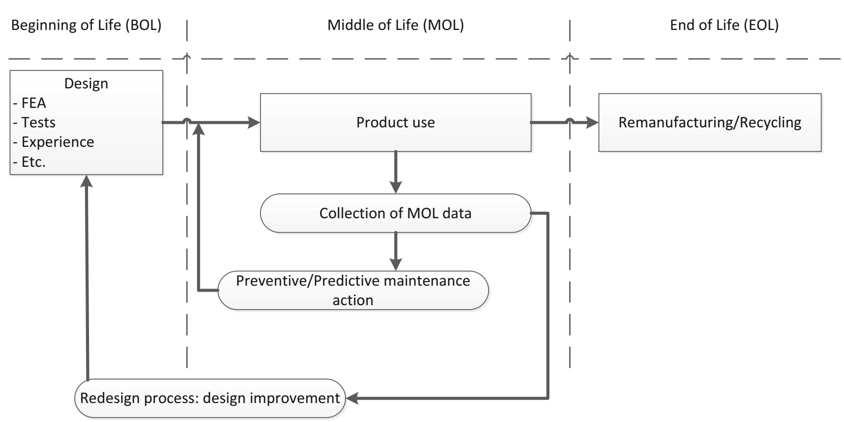



**Fig. 1** Product usage data and its application over the whole product

asymptotic efficiency. They provided insight into the trade-offs between two methods of estimating the quartiles of the time-to-failure distribution and showed that degradation analysis provided more precision results than traditional failure-time analysis. Lee [6] dealt with a methodology that could analyze machine degradation quantitatively. They developed a pattern discrimination model (PDM) based on a cerebellar model articulation controller (CMAC) neural network. Moreover, Xu et al. [7] proposed a new type of neural network, called Fuzzy CMAC to detect the degradation status of a machine. Huang [8] proposed a Bayesian decision process in order to provide a methodology dealing with the decision problems of repairable systems which can determine the conditions for taking different actions. They used a nonhomogeneous Poisson process to describe the behavior of a deteriorating repairable system. Djurdjanovic et al. [9] have addressed many statistical methods such as logistic regression and autoregressive moving average (ARMA) model for performance assessment and prediction in the watchdog agent concept. In addition, Frangopol et al. [10] reviewed the research related to probabilistic models for maintaining and optimizing the life cycle performance of deteriorating structures, with a focus on applications to civil structures and emphasizing highway bridges. Wang and Coit [11] proposed a general modeling and analysis approach for reliability prediction based on degradation modeling, considering multiple degradation measures. Recently, Kara et al. [12] proposed a two-step methodology for estimating the remaining lifetime of components and evaluating their reuse potentials based on life cycle data. They claimed that in the first step, the operating life could be estimated by Weibull analysis based on maintenance data. In the second step, they addressed that several tools such as linear multiple regression, dynamic ordinary Kriging, universal Kriging, Co-Kriging, and neural networks could be applied based on lifetime monitoring data.

On the other hand, there have been various methods for product failure identification: failure modes and effects analysis (FMEA), fault tree analysis (FTA), or failure modes, effects and criticality analysis (FMECA). One of well-known methods is the FMEA method. Its aim is to have a clear overview of end effects that different failure modes have. The FMEA is a widely used technique to systematically identify and investigate the weakness of potential system (product or process). It is especially useful in the conduct of reliability, maintainability, and safety analyses. Such analyses support for examining all the ways in which a system failure can occur, potential effects and consequences of failures on system performances and safety, and the seriousness of these effect. The main point of the FMEA method is to quantify the risk of each failure. This risk analysis is important for decisional process, which takes place at the end of the FMEA method and in which countermeasures or preventive actions must be taken (for more details of FMEA, refer to Kmenta [13]).

In spite of many previous works related to product degradation and failure identification as explored, there are still some limitations. First, there is the lack of research works about how to analyze product degradation status based on gathered product usage data. There is also no suitable guidance or framework for engineers to take appropriate decisions based on degradation status analysis. Koç and Lee [14] said that current approaches have the limitation in detailed methods or validated predictive models for analyzing and detecting the factors that affect degradation of product or machine. Second, there have been little research works on the use of operational data of a product into product design or maintenance until now. Although some methods based on FMEA have been used for identifying design problems during MOL phase, the FMEA-based methods have a critical weak point in the sense that they do not consider product degradation status directly. Most FMEA methods fail to consider the concept of degradation at failure models quantitatively [15]. Failure representation in FMEA is inherently incomplete and not useful for diagnostic inference [16]. The FMEA considers only on/off failure modes, without considering the possibilities of progressive loss of performance, i.e., degradation. For the FMECA, the 100 % performance is considered operative state while the 0 % performance is considered out of operation state. In other words, the classical FMECA restricts the term failure to the one referring to total inability of fulfilling its functional capability. But in reality, before being completely out of function, a product or a system may undergo the progressive loss of performance. Hence, the FMECA has to be adjusted to take into account the impact of degradation.

In this regard, this study focuses on developing the detailed procedure for assessing product degradation based on product usage data and for guiding useful information related to the improvement of product design and maintenance operation.

## 3 Degradation mode and criticality analysis

In this section, a decision support method that can identify the degradation mode and its effect for design improvement and maintenance enhancement, called DMCA, is explained in detail. The DMCA is evolved from FMEA in order to consider product degradation based on product usage data. There are some differences between DMCA and FMEA as follows:

1. FMEA focuses on identifying, prioritizing, and alleviating potential failure modes at the BOL phase before the product reaches the customer, while DMCA focuses on identifying the status change of product performance during product usage period and evaluating its criticality for design and maintenance improvement.
2. FMEA aims to give the feedback to product design before production or product preparation, while DMCA aims to

support not only product design improvement but also maintenance decision during product usage phase.

3. Unlike FMEA, DMCA considers both the product failure and its degradation effect based on product usage data gathered during product operation.

Figure 2 shows the detailed procedure of DMCA. The DMCA procedure consists of four main parts: setup, product degradation mode analysis (PDMA), criticality analysis (CA), and decision and action (DA). At the first part (setup) the basic understanding of the target product is developed. The degradation characteristics of the targeted product are analyzed in the second part (PDMA). The evaluation of degradation is done in the third part (CA). At the last part (DA), the decision process for design improvement and maintenance is done.

The following are notations used in this study and the detailed procedure of DMCA.

**Notation**

| | |
|---|---|
| $S$ | Severity index |
| $D$ | Detection index |
| $O$ | Occurrence index |
| $OH$ | Outage index |
| $DR$ | Degradation rate index |
| $CRIT$ | Criticality index |
| $T$ | Time |
| $P$ | Performance indicator |
| $P(t)$ | Value of performance indicator at a specific time $t$ ($0 \le P(t) \le 1$) |
| $P_R(t)$ | Real performance value estimated at time $t$ |
| $x_n$ | Parameters related to a performance indicator |
| $D(t)$ | Degree of degradation at time $t$ |
| $P_E(t)$ | Theoretically expected performance value at time $t$ in product design |
| $T(t)$ | Remaining lifetime of the lift arm structure |
| $T_R(t)$ | Real remaining lifetime estimated at time $t$ |
| $T_E(t)$ | Theoretically expected remaining lifetime at time $t$ in product design |

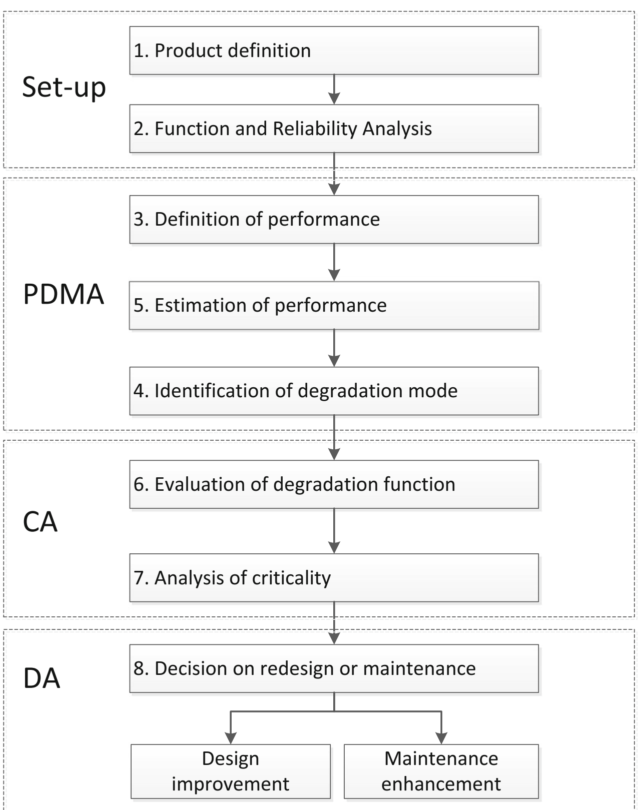



**Fig. 2** DMCA procedure

### 3.1 DMCA procedure

Step 1. Product definition

At first, it is necessary to define a target product and describe its basic specifications. Here, the product can be a component, or an assembly part, or a whole one itself. The model name, main function, key specifications, and operation conditions of the target product should be clarified in this step.

Step 2. Function and reliability analysis

To grasp the characteristics of the product, it is necessary to decompose the target product into its subassemblies and their relations and to define relevant functions. After identifying product functions, it is necessary to find the related subassemblies that realize functions and to analyze the relations between these subassemblies. This analysis is required in order to support the inference mechanism that helps to find the locations and causes of degradations when a function does not work as expected. In this step, analytic modeling tools such as function-behavior-state (FBS) model proposed by Umeda et al. [17] or the reliability block diagram (RBD) (sometimes called a "functional block diagram") could be used.

Step 3. Definition of performance

To calculate the degradation of the target product, first of all, it is prerequisite to define what can be the performance indicator of the target product and which parameters affect the performance in a suitable manner. According to main concerns on the target product, various performance indicators could be defined for the target product. For example, the horse power of a truck engine from the strength aspect or its lifetime from the durability aspect could be a performance indicator of a truck engine. According to the objective of analysis, the performance of the target product should be defined clearly by the specific performance indicator. Also, it should be representable with related parameters in a quantitative manner.

Step 4. Estimation of performanceTo clarify the performance for the target product, the following procedure should be carefully done in a stepwise manner:

1. Define the performance of the target product

   The performance depends on which aspect of the product you want to analyze. According to the purpose of analysis, the most relevant characteristics of the product that precisely represent the product status should be identified. For example, in case that engineer wants to analyze product reliability, failure-related notion could be the performance of the target product.
2. Select the performance indicator representing the status of the product

   In defining performance, it should be also considered that the selected performance can be measurable as a numerical value. To represent performance as a numerical value, it is necessary to define an appropriate performance indicator having a numerical value and manipulated by the gathered usage data. According to the kind of performance indicator, it can be calculated by single sensor data or by the complex combination with several kinds of usage data.
3. Find the parameters ($x_n$) which are related with the performance indicator

   During product operation, various kinds of data can be generated and gathered or obtained from previous data: product degradation state data, operation data, working environment data, and future usage mode data. Some of them are closely related with the performance indicator of the target product so that they become the parameters for the performance indicator. To estimate the value of performance indicator in a precise manner, it is important to identify the most relevant parameters from available product data.
4. Specify relations between the performance indicator of the target product and its parameters

   In order to estimate the value of the performance indicator in a precise manner, the relations between parameters and the performance indicator should be clarified. They must be represented as the form of the mathematical function.
5. Define a performance function

   The performance indicator at a certain time $t$ can be represented as the mathematical function as like the following Eq. (1). According to Eq. (1), the performance indicator is affected by the parameters nominated as $x_n$.

$$P(t) = f(x_1, x_2, x_3, \cdots, x_n; t) \tag{1}$$

6. Calculate the performance

   Based on the defined performance function and gathered data, the performance of the target product can be calculated as a numerical value.

Step 5. Identification of degradation mode

In general, the degradation is defined as the loss of performance from its original status. When the performance function is defined, the degradation (or deterioration) can be easily calculated as shown in Fig. 3.

The degradation mode is defined as the way or manner in which the degradation of a product (or subassembly, component) can occur. In this study, one aspect of degradation mode, the fitness of degree of degradation is focused. The fitness of the degree of degradation is measured by the difference between the degree of real degradation in product usage and the degree of expected degradation in product design. During the development of a product, the degradation is designed to a certain degree since it is inevitable and occurs naturally as operation time increases. According to the expected degradation in product design, the life cycle activities such as suitable maintenance schedule can be planned. However, in reality, the degree of degradation may be more or less than expected. The problem happens when the degradation is too much deviated from the planned degree. Thus, it is important to identify the unacceptable degradation mode. This aspect of degradation mode is considered in this study. The degradation mode shows how a product becomes

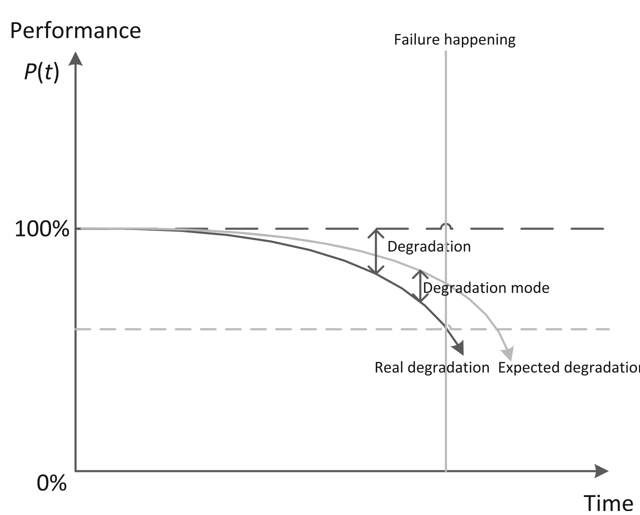



**Fig. 3** Performance and degradation

damaged during usage period compared to the expected by design. The degree of degradation at the specific time $t$ is calculated by the following Eq. (2). This value is used to evaluate the degradation function of a product in the step 6.

$$D(t) = \frac{P_R(t)}{P_E(t)} \quad (2)$$

According to the value of $D(t)$, there are three kinds of degradation modes as follows:

1. $D(t)>1+\varepsilon$: the rate of degradation is less than the expected.
2. $1-\varepsilon\leq D(t)\leq 1+\varepsilon$: the rate of degradation is similar to that of the expected.
3 $0\leq D(t)<1-\varepsilon$: the rate of degradation goes beyond the expected.

If $D(t_1)<D(t_2)$, then the degree of degradation at $t_2$ is less than that at $t_1$. If $D(t_1)>D(t_2)$, then the degree of degradation at $t_2$ is much than that at $t_1$.

Step 6. Evaluation of degradation function

According to the value of $D(t)$, the impact on the degradation in a certain interval ($t_1$, $t_2$) can be evaluated with the following criteria.

1. $\int_{t_1}^{t_2} D(t)dt/(t_2-t_1) > 1+\varepsilon$: the degradation goes on slowly than expected.
2 $1-\varepsilon\leq\int_{t_1}^{t_2} D(t)\,dt/(t_2-t_1) \leq 1+\varepsilon$: the degree of degradation is normal.
3 $\int_{t_1}^{t_2} D(t)dt/(t_2-t_1) < 1-\varepsilon$: the degradation goes much farther than expected.

Step 7. Analysis of criticality

The FMEA method uses the risk priority number (RPN) to assess the importance of failure and its impact. In the DMCA, the *CRIT* index is proposed in order to assess the degree of degradation and the degree of criticality during product usage period. The *CRIT* is defined as a function of five indexes (severity ($S$), detection ($D$), occurrence ($O$), outage ($OH$), and degradation rate ($DR$)) as follows:

$$CRIT = S\cdot D\cdot O\cdot OH\cdot DR \quad (3)$$

The first three indexes, $S$, $D$, and $O$, are the same as those of the RPN calculation in the FMEA except that focusing on degradation. In the *CRIT*, the $OH$ and $DR$ are newly introduced to consider the impact of various degradation modes. Based on the *CRIT*, an engineer can detect how much critical the degradation is and whether the causes of degradation has to be corrected or not in product design and maintenance.

Severity index ($S$). The severity index expresses how serious the effect of the degradation on a product is. The degradation of a product can give rise to dangerous situations to the environment around the product or to the other subassemblies (parts). As the impact of degradation increases, the severity has higher value. The range of severity is confined on a scale of 1 to 10 as like the severity rating for a failure mode.

Detection index ($D$). The detection index expresses the degree of tendency related to how well potential degradation mode will be detected before a product-level failure occurs. The value of $D$ can be rated on a scale of 1 to 10 as like the severity rating for a failure mode.

Occurrence index ($O$). The occurrence index expresses the degree of tendency as to how often degradation happens. It is proportional to the frequency (or period) of appearance of the degradation mode. The value of $O$ can be rated on a scale of 1 to 10 as like the occurrence rating for a failure mode.

Outage index ($OH$). It indicates the degree of the negative effect of outage time that takes for solving degradation problems. The outage time means the lead time from product failure to product recovery, i.e., complete stoppage time of the product operation as shown in Fig. 4. The stop of product operation can imply some financial problems to the customer since the replacement of the

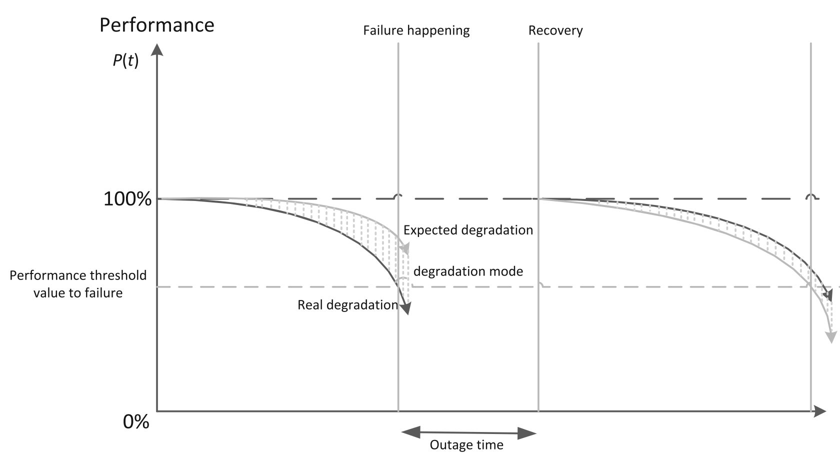



**Fig. 4** Outage time and degradation mode

failed product cannot be always instantaneous, and it will imply some delays on the customer work. The *OH* is rated on a scale of 1 to 10 as shown in Table 1:

Note that, for the same degradation, the *OH* can take different values because of the warranty coverage. When the product becomes older, its warranty coverage decreases and the financial impact of the failure on the customer becomes stronger. The fact that the work can be stopped for a certain time (before product replacement or repair) implies the delay in the customer work. Even though the warranty coverage provides a financial compensation, a big delay can cause customers' dissatisfaction.

Degradation rate index (*DR*). The *DR* indicates the performance loss of the product during the product usage period. The value of *DR* implies the degree of difference between real degradation value in field and expected one by product design, which causes an increase of product design improvement time or maintenance time or the waste of product cost due to over-dimensioned design. The *DR* is calculated as follows.

$$DR = \sum_{i=1}^{n} \frac{\int_{t_{i-1}}^{t_i} D_i(t)dt}{t_i - t_{i-1}} \tag{4}$$

where $t$ is the observation time.

The value of *DR* indicates the average of degradation rates during some operation time $(t_0, t_n)$. The rating of *DR* is shown in Table 2.

Criticality index (*CRIT*). The *CRIT* gives the degree of relative criticality on the target product. It indicates the global impact of degradation status on the target product. The value of *CRIT* index varies from 1 to 100,000 since the *CRIT* index is calculated by the multiplication of five indexes. Based on the value of *CRIT*, engineers can recognize the most urgent critical product (or subassemblies, component, etc.) and can prepare design modification or preventive maintenance action. If the *CRIT* value is bigger than a certain threshold value, causes of relevant indexes affecting the value should be examined and corrected. To give the reference on the *CRIT* value, a guideline for *CRIT* which is extended from the evaluation method of RPN index [18] is explained in Table 3.

**Table 1** Outage (*OH*) index

| Outage (*OH*) | Rating |
|---|---|
| Minor/low: The downtime does not cause work delay. | 1<br>2 |
| Moderate: The downtime involves some amount of work delay times, but not serious. | 3<br>4<br>5<br>6<br>7<br>8 |
| High/very high: The downtime causes the long work delay until the product is recovered from the critical damage throughout reparation including part/product changes. | 9<br>10 |

**Table 2** Degradation rate (*DR*) index

| Degradation rate (*DR*) | Rating |
|---|---|
| Moderate: The value of degradation rate index is around 1, which means that the tendency of performance loss is similar to the expected in $(t_0, t_n)$. | 1<br>2<br>3 |
| Minor/low: The value of degradation rate index is higher than 1, which means that the degree of performance loss is less than expected in $(t_0, t_n)$. | 4<br>5<br>6 |
| High/very high: The value of degradation rate index is lower than 1, which means that the degree of performance loss goes beyond the expected in $(t_0, t_n)$. | 7<br>8<br>9<br>10 |

DMCA worksheet. It is important to manage and control the values of five indexes in *CRIT*. To this end, the following DMCA worksheet template is proposed as shown in Table 4. The DMCA sheet helps engineers to understand the degradation, find related function, and evaluate its criticality.

Step 8. Decision on redesign or maintenance

During product operation, the parameters related with performance could be monitored and measured by smart embedded information device and various sensors attached to the product so that the $D(t)$ and *CRIT* could be calculated and evaluated, respectively. These two values can be used to decide whether some actions such as product redesign and preventive/predictive maintenance are needed to relieve unexpected degradation and its effect or not. The value of $D(t)$ evaluates the degradation state while the *CRIT* evaluates the degradation effect. The decision process is triggered by $D(t)$ and *CRIT*. To check whether the targeted product is able to reach its design goal or not, the degradation status of the product should be evaluated. Depending on the degradation function, there are three ways of evaluations: if $D(t)<1-\varepsilon$, the product status is inadequate due to under-dimensioned design or hard use. If $1-\varepsilon<D(t)<1+\varepsilon$, then the product status is adequate. Otherwise, the product can be regarded as over-dimensioned design or loosely used. If $D(t)<1-\varepsilon$ or $D(t)>1-\varepsilon$, then the

**Table 3** Guide for *CRIT* assessment

| Cases of assessment rating | | | | | Evaluation | Action taken |
|---|---|---|---|---|---|---|
| *S* | *D* | *O* | *OH* | *DR* | | |
| 1 | 1 | 1 | 1 | 1 | Ideal situation (goal) | N/A |
| 10 | 1 | 1 | 1 | 1 | Degradation does not hamper user's work. | N/A |
| 1 | 10 | 1 | 1 | 1 | Assured mastery | N/A |
| 1 | 1 | 10 | 1 | 1 | Frequent degradations, but not influential | N/A |
| 1 | 1 | 1 | 10 | 1 | Costly, but rare | Yes |
| 1 | 1 | 1 | 1 | 10 | Design improvement is required. | N/A |
| 10 | 10 | 1 | 1 | 1 | Degradation hampers user's work. | Yes |
| 10 | 1 | 10 | 1 | 1 | Design improvement is required due to frequent degradations with major impact. | Yes |
| 10 | 1 | 1 | 10 | 1 | Costly | Yes |
| 10 | 1 | 1 | 1 | 10 | Severe problem in design | Yes |
| 1 | 10 | 10 | 1 | 1 | Frequent degradations with the difficulty of detection may hamper user's work. | Yes |
| 1 | 10 | 1 | 10 | 1 | Failure due to degradation can cause serious problems. | Yes |
| 1 | 10 | 1 | 1 | 10 | Design improvement is required | Yes |
| 1 | 1 | 10 | 10 | 1 | Frequent degradations with severe impact: design improvement and preventive maintenance are required. | Yes |
| 1 | 1 | 10 | 1 | 10 | Frequent degradations: design improvement and preventive maintenance are required. | Yes |
| 1 | 1 | 1 | 10 | 10 | Design improvement is required. | N/A |
| 10 | 10 | 10 | 1 | 1 | Trouble! | Yes |
| 10 | 10 | 1 | 10 | 1 | | |
| 10 | 10 | 1 | 1 | 10 | | |
| 10 | 1 | 10 | 10 | 1 | | |
| 10 | 1 | 10 | 1 | 10 | | |
| 10 | 1 | 1 | 10 | 10 | | |
| 10 | 10 | 10 | 10 | 1 | | |
| 10 | 10 | 10 | 1 | 10 | | |
| 10 | 10 | 1 | 10 | 10 | | |
| 10 | 1 | 10 | 10 | 10 | | |
| 10 | 10 | 10 | 10 | 10 | | |

effect of degradation should be also evaluated by the value of *CRIT*. In the case that the value of *CRIT* is greater than a certain threshold value, it is necessary to take suitable decisions of what action must be set up. There are two types of actions: (1) preventive/predictive maintenance throughout developing and analyzing maintenance cost models and (2) design improvement throughout the detailed analysis to find the design problem which affects degradation. The details of decision process are described in Fig. 5.

**Table 4** DMCA worksheet

| No. | Item | Description | Index value |
|---|---|---|---|
| 1 | Target product | Description on target product | – |
| 2 | Function | Function descriptions of target product | – |
| 3 | Potential degradation | Description of potential degradation mode | – |
| 4 | Potential causes | Description of potential degradation causes | – |
| 5 | Potential effects | Description of potential effects due to degradation | – |
| 6 | Degree of detection (*D*) | Degree of difficulty in detecting the degradation | |
| 7 | Degree of occurrence (*O*) | Degree of how often degradation happens | |
| 8 | Degree of severity (*S*) | Degree of severity due to degradation | |
| 9 | Degree of outage (*OH*) | Degree of length of stoppage time | |
| 10 | Degree of degradation (*DR*) | Degree of degradation value | |
| 11 | Degree of criticality (*CRIT*) | Degree of criticality due to degradation | |
| 12 | Degradation function ($D(t)$) | Degree of degradation at a specific time $t$ | |
| 13 | Action item | Description on required action | – |

## 4 Case study

To show the validity of the proposed approach, this section introduces a case study based on a heavy construction equipment vehicle produced by the *C* company in France. In EU FP6 PROMISE project, the *C* company had developed an application of product embedded information devices (*on-board computer* and *RFID tags*) with crack propagation sensors attached to a structural part of the heavy construction equipment vehicle in order to gather its usage status. The heavy construction equipment vehicle focused in this case study is the track-type loader (TTL) that has a lift arm equipped with a bucket to lift loads. The principal limitation of the information flow for the TTL is that usage information can be collected only when maintenance service triggered by a failure is performed. No other information regarding the TTL operation is collected if no failure happens. If the same failure is observed more than three times, a continuous product improvement (CPI) process starts to analyze the causes of the failure in detail. However, still, there is no way to check whether the TTL product is adequately operated or not. To overcome this limitation, the company wants to gather usage information of the TTL and transform them into suitable information and knowledge for feedback actions for design, maintenance, or reuse/recycle stages, which improves MOL responsiveness to improve

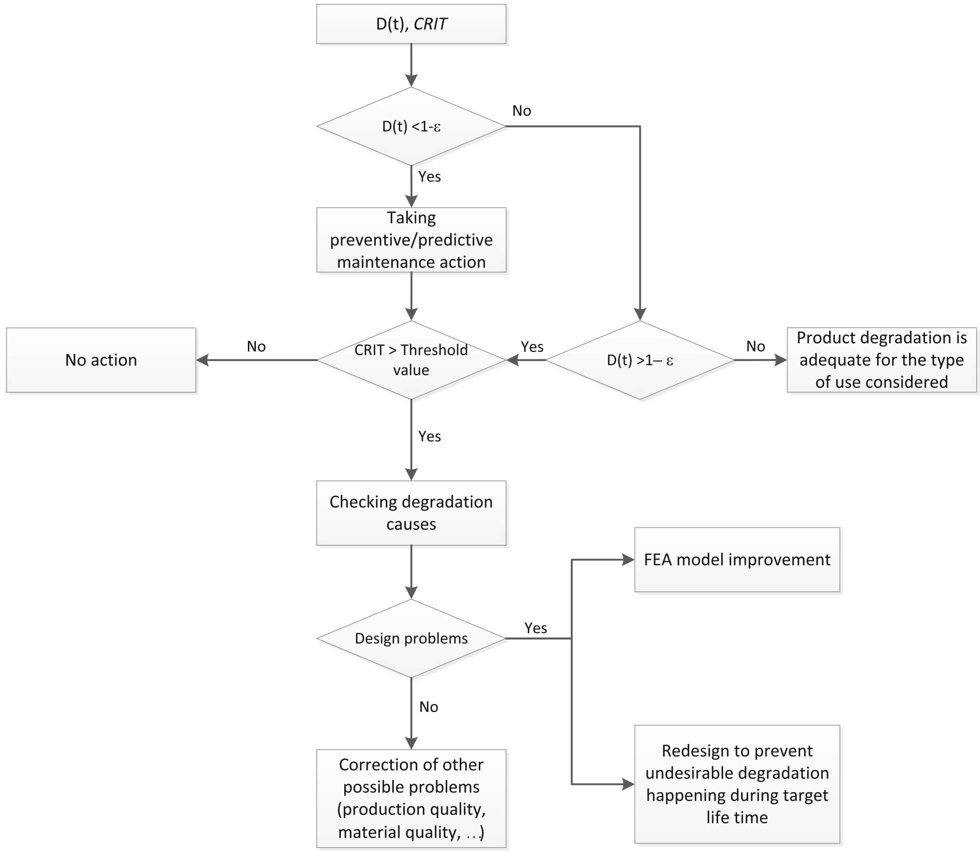



**Fig. 5** Decision process

customer requirements. In this case study, the proposed DMCA approach is applied as follows.

Step 1. Definition of target product

The targeted product in this case study is the structural assembly of the lift arm of the TTL. It is composed of the following parts: two lateral arms, one cross member, eight linkage pins, and one lever system that consists of lever and load transmission bar.

Step 2. Function and reliability analysis

The lift arm supports the following two basic functions: one is to lift the bucket and the other is to rotate the bucket. Figure 6 shows functional block diagrams of the lift arm.

Even though not many failures are observed in this part, the occurred failure causes serious problems and requires long maintenance time. Generally, the overall lifetime of lift arm is expected as 8000 h.

Step 3. Definition of performance

In general, various performance indicators of the mechanical structure can be defined, e.g., structure rigidity, structure mechanical resistance, and structure lifetime. For the lift arm structure, the performance indicator could be the maximum load that the lift arm can support without deformation or breaking, for example, when a big load is transported in the bucket or when the bucket is pushed against hard material. The performance indicator considered in this study is the remaining lifetime of the lift arm structure. The remaining lifetime is the time until when the lift arm cannot provide its function normally. At each instance of the lift arm life, its remaining lifetime depends on various factors such as current degradation state, usage behavior data, and future user model. It is easy to understand that the less degradation, the more durable remaining lifetime. We can also say that the harder future working conditions, the less durable remaining lifetime.

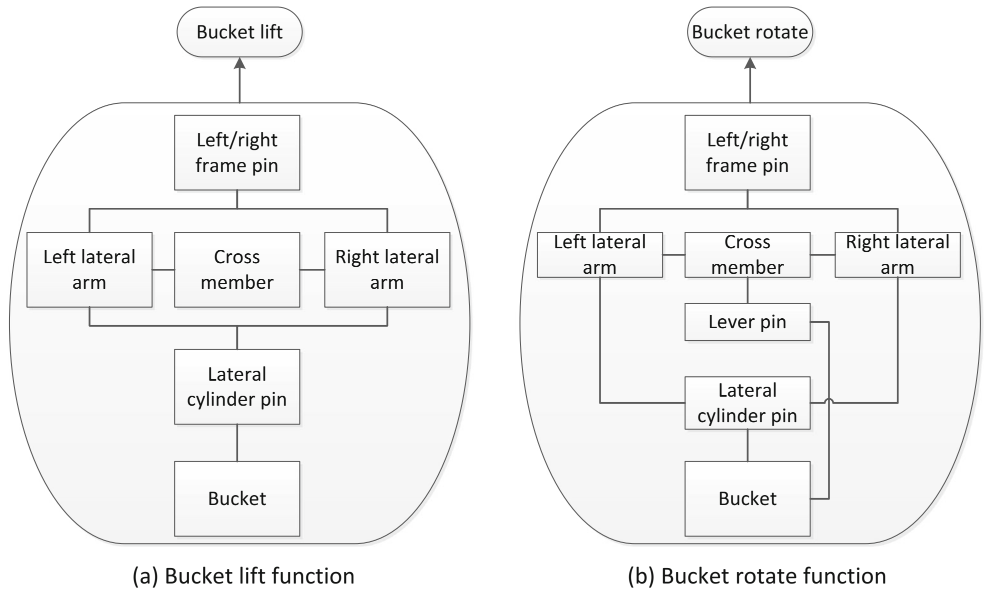
Step 4. Estimation of performance

The real remaining lifetime of lift arm structure at a certain time $t$ ($T_R(t)$) could be estimated based on degradation state data by crack propagation sensors, future usage mode data, and mission profile data as shown in Eq. (5).

$$T_R(t) = f(\text{degradation state, operation, working environment, future usage mode}; t) \quad (5)$$

To estimate the product performance in a more exact way, it is necessary to understand the concept of product mission profile. The mission profile data consist of operation data and

**Fig. 6** Functional block diagram of lift arm




working environment data. The degradation state data is the crack propagation data measured by sensors. To assess the degradation state of the lift arm, it is necessary to use several sensors attached to different locations of structure welds. Each sensor observation provides the measurement value related to the *degradation state* of each location. The sensor provides the information at each ligament breaking during the time of use of the structure part. One ligament breaking corresponds to 8.33 % of sensor damaging.

The operation data indicates usage behavior data generated from product consumers or operators under a specific usage mode and collected by various sensors attached to the TTL during its operation, e.g., engine revolution per minute (RPM), mileage, operation hours, the number of engine starts, and several loading conditions such as hydraulic cylinders pressure measurement, pin load sensor measurements, and hydraulic cylinders displacement measurements. The working environment data are related with working places where the product is usually used. As working environment data, geographical data in the product working site such as humidity, temperature, and soil type could be collected. The future usage mode data are the predefined working conditions for future use, e.g., economic mode or sport drive mode in a car. For the TTL case, as the future usage mode, the following can be considered: waste transfer, forestry, road construction, quarry, ship hold, demolition (building), house construction, and so on. To select the future use mode of the structure part means to decide at the present instant what future mission will be realized.

Without the detailed identification and segmentation of the mission profile and the selection of future usage mode, it is difficult to estimate the remaining lifetime in an exact way. Some TTLs are used in the harsh environment or under strict usage operations while others are used in the mild environment or under loose usage operations. Thus, depending on environmental and operational conditions, the degradation will be different, which indicates that the estimation of product performance should be done considering mission profile data and future usage mode data.

Based on the selected usage mode, a typical segmentation of mission profile data is established and each one is stored in a database called the mission profile database for reuse. When the future usage mode is decided, the corresponding mission profile data can be retrieved from the mission profile database and used for the estimation of remaining lifetime.

The remaining lifetime, in this case study, can be estimated by how much fatigue is accumulated at the lift arm structure and how much cyclic stress can be applied until fatigue fracture happens. To check the current status of fatigue accumulation, the crack propagation sensor is attached. As the cyclic stress is given, the crack in the crack propagation sensor grows so that the length of crack in the sensor indicates how much fatigue is accumulated. The expecting stress in the future is estimated by the mission profile and the finite element analysis (FEA). The external loads on structure pins are compared with those of the mission profiles, and the matched mission profile provides a set of external loads. The extracted external loads are combined with the CAD model of structure pins, and a stress profile history can be analyzed by FEA (see Fig. 7).

The result of FEA allows retrieving the future local stress burden at each location of the structure, and in particular at the targeted sensor measurement point. When the future local stress profile is found, the remaining number of applied stress cycles can be calculated by the fracture mechanics theory (see Appendix) based on current degradation state data by sensors and so the local remaining lifetime can be estimated. The more

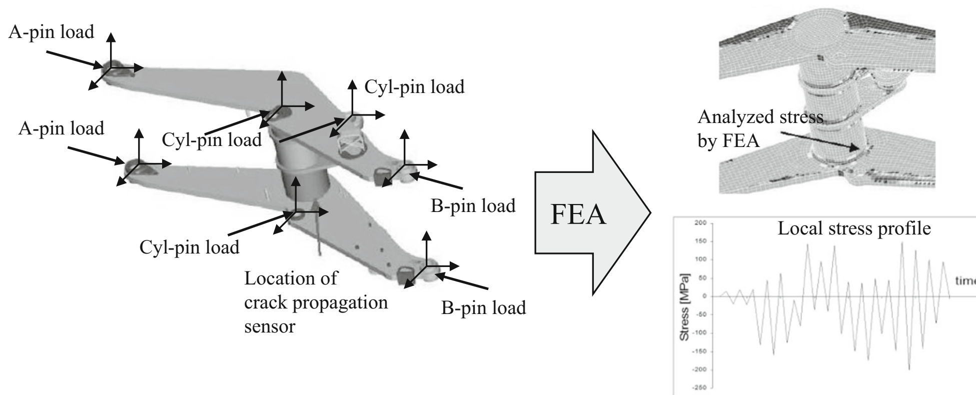



**Fig. 7** Sensor data for mission profile classification and FEA

detailed procedure for estimating the remaining lifetime is explained in the Appendix. Figure 8 shows the procedure as to how to estimate the remaining lifetime.

Step 5. Identification of degradation mode

The critical locations of the lift arm structure are welded joints which have the highest stress levels. The welded joints are as follows: welds between the cross member and two lateral arms, welds for pin reinforcements on lateral arms, and welds for bosses (for hydraulic lines). At these welded joints, the *C* company wants to use the crack propagation sensor that can measure the length of crack propagation for estimating the remaining lifetime of the welded joint. This study assumes that the remaining lifetime of the lift arm structure can be determined by the smallest local remaining lifetime among those of different weld locations. For the convenience of handling, this study focuses on a weld point between the cross member and two lateral arms and regards the estimated remaining lifetime of the weld point as that of the lift arm.

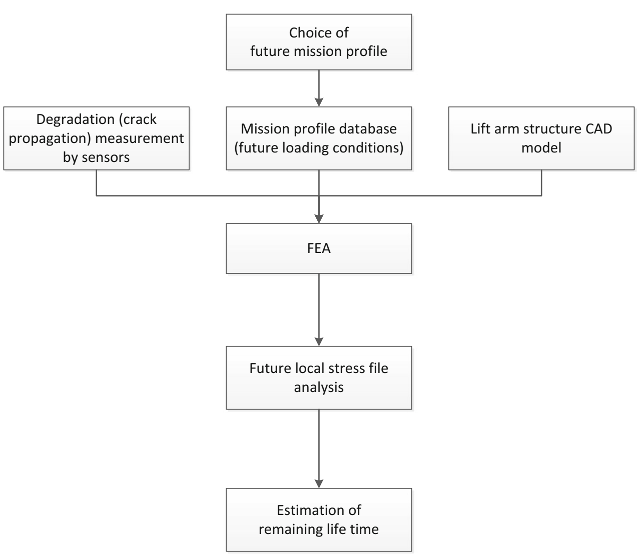



**Fig. 8** Remaining lifetime estimation of lift arm (see Appendix)

For each observation time *t*, the degradation function of this case study takes the following form.

$$D(t) = \frac{T_R(t)}{T_E(t)} \tag{6}$$

where $T_E(t)$ indicates the theoretically expected remaining lifetime at time *t* and $T_R(t)$ indicates the estimated remaining lifetime at time *t*. In this study, it is assumed that $T_E(t)$ could be obtained from the reliability tests in product design and $T_R(t)$ could be estimated by the algorithm of Cattaneo [19] (refer to Appendix) based on gathered product-related data. Figure 9 depicts how degradation function is made.

Step 6. Evaluation of degradation function

To evaluate the degradation function of the weld area of lift arm structure, the value of $D(t)$ is calculated by the comparison between theoretically expected remaining lifetime and estimated remaining lifetime based on the data of crack propagation sensor, as shown in Table 5.

In Table 5, the values of $T_E(t)$ were generated in product design and the values of $T_R(t)$ were estimated by the algorithm (refer to Appendix) based on crack propagation sensor data. For example, the value of $D(3600)$ can be calculated as follows:

$$D(3600) = \frac{6424}{6100} = 1.05 \tag{7}$$

Figure 10 shows that there is not big difference between the expected remaining lifetime in product design and the estimated one in a field. This result shows that the

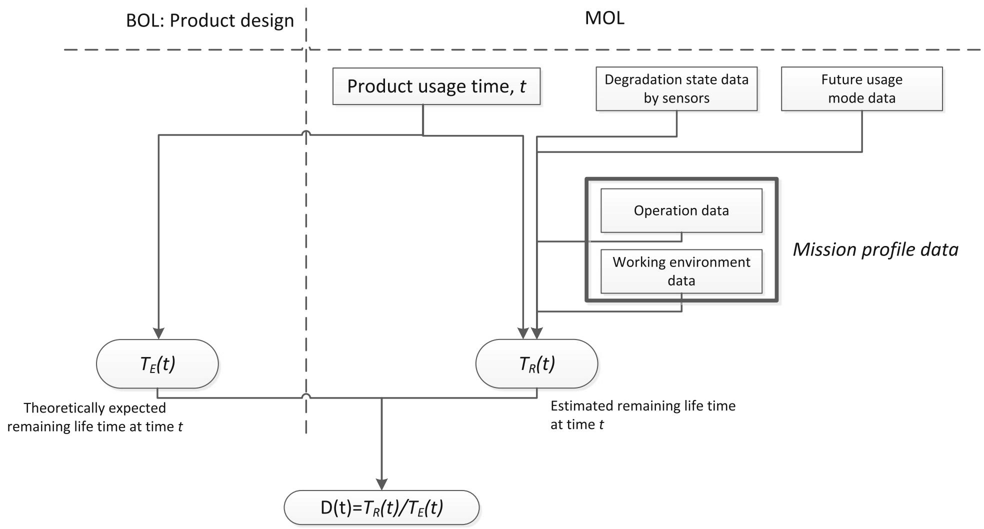



**Fig. 9** Calculation of degradation function value

target product has been properly used, and there is no urgent requirement on maintenance or product design at the moment. Figure 11 depicts the values of $D(t)$ depending on usage time of lift arm structure. The main observation is that the value of $D(t)$ rapidly goes down after $t$=5300. It tells us that it is necessary to carefully look into the reason for the abrupt decreasing tendency.

Step 7. Analysis of criticality

In order to analyze the criticality, at first, the rating values of $S$, $D$, $O$, $OH$, and $DR$ indexes are evaluated, respectively. Table 6 shows the evaluation result of five indexes.

The value of $DR$ index after 3600 usage time is calculated as follows:

$$DR = \frac{((600-0)\times(0.95+0.97)2\ )}{3600} + \frac{((1300-600)\times(0.97+1.01)2\ )}{3600} + \frac{((2200-1300)\times(1.01+1.01)2\ )}{3600} + \frac{((2600-2200)\times(1.01+1.02)2\ )}{3600} + \frac{((3600-2600)\times(1.02+1.05)2\ )}{3600} = 1.005$$

Here, the value of $D(t)$ is roughly estimated by linear approximation rather than calculating integrals in an exact way since gathered crack propagation sensor data had been measured in a discrete way. To this end, it is assumed that the value of $D(t)$ between two time points is linearly changed. To calculate the integral area of $D(t)$, the trapezoidal formula is used.

According to the result of Table 7, the value of $CRIT$ index is calculated as follows:

$$CRIT = 10\times1\times2\times9\times1 = 180 \tag{9}$$

After 3600 usage time, the below DMCA sheet is made in order to evaluate the degradation mode and its effect on the weld area between lift arm and cross member.

Step 8. Decision on redesign or maintenance

The value of $D$(3600) is 1.05. Under $\varepsilon$=0.20, this value means that the degradation status on the weld area is appropriate compared to the expected one. The value of $CRIT$ index is 180, also not serious. However, it is necessary to understand how this value is generated. Looking into the $CRIT$ index calculation, the values of $S$ and $OH$ are the main reasons to increase the value of $CRIT$ because the failure of lift arm structure gives rise to very severe impacts due to long time of reparation process time. Hence, it is necessary to consider the way of improving stability on the weld area and reducing its reparation process time, e.g., by the optimization of maintenance logistics and maintenance planning, from the long-term viewpoint. Furthermore, it is necessary to do preventive/predictive maintenance policy in a periodic way, i.e., monitoring the welding area in a certain interval and analyzing the crack status for preventing the critical failure. Considering the values of $O$ and $DR$, there is not specific maintenance action required at the moment. In case that redesign is required, the stress profile extracted from the mission profile and FEA can provide a clue to find solution for design improvement. If a high stress is found by

**Table 5** Example of $D(t)$ calculation

| $t$ | $T_E(t)$ | $T_R(t)$ | Crack length coefficient by sensor (mm) | $D(t)$ |
|---|---|---|---|---|
| 0 | 8000 | 7633 | 0 | 0.95 |
| 600 | 7700 | 7506 | 0.2 | 0.97 |
| 1300 | 7300 | 7379 | 0.4 | 1.01 |
| 2200 | 6900 | 6997 | 1 | 1.01 |
| 2600 | 6500 | 6615 | 1.6 | 1.02 |
| 3600 | 6100 | 6424 | 1.9 | 1.05 |
| 4100 | 5600 | 6043 | 2.5 | 1.08 |
| 4900 | 5100 | 5725 | 3 | 1.12 |
| 5300 | 4400 | 5089 | 4 | 1.16 |
| 6200 | 3600 | 3816 | 6 | 1.06 |
| 7100 | 2400 | 2226 | 8.5 | 0.93 |
| 7600 | 1100 | 954 | 10.5 | 0.87 |
| 8000 | 0 | 191 | 11.7 | 0 |
| Stress level ($\Delta\sigma$) | 50 Mpa | Stress intensity factor ($\Delta K$) by $\Delta K = \beta\cdot\Delta\sigma\cdot\sqrt{\pi\cdot a}$ | | 3.96 |
| Correction factor ($\beta$) | 0.5 | | | |
| Crack length coefficient ($a$) | 0.008 m | | | |
| Crack growth rate ($\dot{a}$ of $\dot{a}\cong\frac{da}{dN} = C(\Delta K)^m$) | 0.000126 | Empirical parameter ($C$) | | 0.0000295 |
| | | Empirical parameter ($m$) | | 1.053 |
| Planned lifetime ($T_L$) | 8000 h | | | Remaining lifetime by $T_R(t) = T_L\cdot\frac{\Delta N}{F}$ |
| The number of stress cycles ($F$) | 100,000 cycle | | | |

FEA, the modification of parts and welds geometry or material change could be done as redesign actions. Table 8 shows some design modification guidance that describes design parameters having influence on the paris equation.

The DMCA approach has the meaning in the fact that it is a systematic approach applying product usage data into maintenance planning and product design improvement. The DMCA approach could provide the guidance for maintenance schedule and product design based on the assessment on the criticality of degradation. The values of *DR* and *CRIT* could be used to evaluate the previous and current status of product in terms of performance degradation. These values could also indicate the risk of product operation in the future. The *DR* value evaluates the degree of soundness related to product degradation. If the *DR* value is higher compared to the expected, then the target product has not been overly used or over-designed considering the field situation. If it is lower than the expected, then it

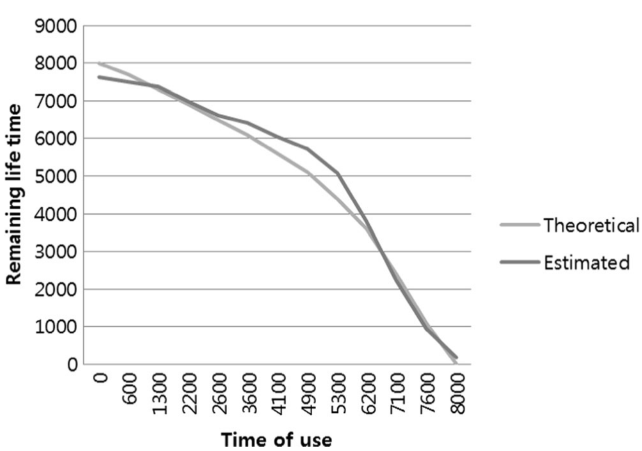



**Fig. 10** Comparison between theoretically expected remaining lifetime and estimated one

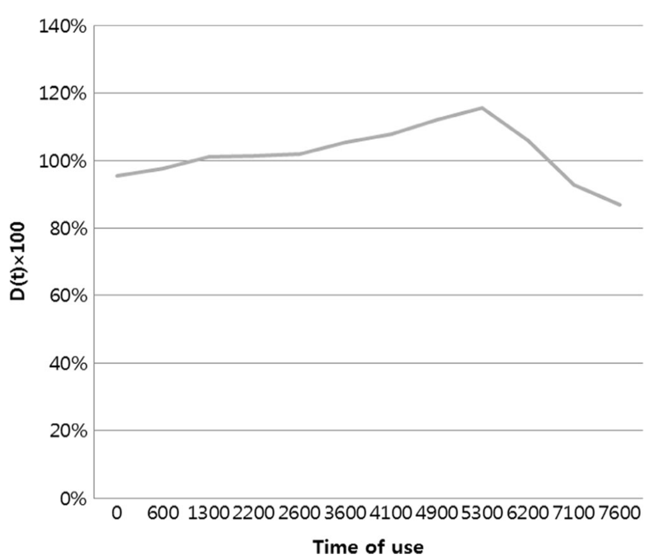



**Fig. 11** The values of $D(t)$ depending on usage time

**Table 6** Example of *CRIT* index evaluation

| Parameters | Result |
|---|---|
| Severity (*S*) | 10 (very severe) |
| Detection (*D*) | 1 (easy to find by the crack propagation sensor) |
| Occurrence (*O*) | 2 (slowly happen) |
| Outage (*OH*) | 9 (long period to repair) |
| Degradation rate (*DR*) | 1 (based on the value of *DR* 1.005) |

has been overly used or under-designed. The *CRIT* value gives us the integrated information on product status considering the degree of detection, occurrence, severity of product failure, outage time, and degradation. Although the DMCA could give users the guidance for the suitable time for maintenance action or the necessity of design improvement based on the assessment of product degradation, it has the following limitations. It does not provide the best time for maintenance action in terms of economic viewpoint. It just tells us the guidance of product degradation status and the criticality in terms of product performance at a certain time. Furthermore, it does not tell us which design of part and how it should be modified.

**Table 7** DMCA check sheet

| No. | Item | Description | Index value |
|---|---|---|---|
| 1 | Target product | Weld area between lift arm and cross member | – |
| 2 | Function | Connection between lift arm and cross member | – |
| 3 | Potential degradation | Crack occurrence | – |
| 4 | Potential causes | Cyclic stress | – |
| 5 | Potential effects | Disconnection between lift arm and cross member | – |
| 6 | Degree of detection (*D*) | Exact detection with the use of crack propagation sensor (1) | 1 |
| 7 | Degree of occurrence (*O*) | Crack occurrence rate is relatively low (2) | 2 |
| 8 | Degree of severity (*S*) | Work stoppage due to loss of functionality of lift arm (10) | 10 |
| 9 | Degree of outage (*OH*) | Maintenance cost is very high because high-cost equipments are required for repair (9) | 9 |
| 10 | Degree of degradation (*DR*) | Degradation status is normal (1, $DR$=1.005) | 1 |
| 11 | Degree of criticality (*CRIT*) | Expected cost is very high when problem happens (360) | 180 |
| 12 | Degradation function ($D(t)$) | Crack propagation status is normal (1.05) | 1.05 |
| 13 | Action item | No action is required at the moment. | – |

**Table 8** Design modification guide

| Parameter types | Physical properties | Modifiable design parameters |
|---|---|---|
| Parts geometry | $\Delta\sigma$: Applied rigidity<br>-Arms rigidity<br>-Cross member rigidity<br>-Pin rigidity | -Arms thickness (profile)<br>-Arms width (profile)<br>-Cross member thickness<br>-Cross member width<br>-Cross member diameter<br>-Cross member relative position |
| Welds geometry | $\beta$: Correction factor to the crack geometry and loading conditions | -Cross member/arms welds radius |
| Parts material | $\Delta\sigma$: Applied load<br>-Arms rigidity<br>-Cross member rigidity<br>-Pin rigidity | -Arms material<br>-Cross member material<br>-Pin material |
| Welds material | $\Delta\sigma$: Applied load<br>$c,m$: Constant for the Paris equation<br>-Weld rigidity | -Cross member/arms welds material |

## 5 Conclusion

This study has dealt with a decision support method for identifying product degradation status considering product usage data. It is important to resolve this research issue because it will provide the capability to make effective decisions as to product design and maintenance considering MOL data. Providing these capabilities can reduce costs, satisfy customers' requirements, and improve operational performance and efficiency over the whole life cycle. Eventually, it will improve customer satisfaction, achieve operational excellence, and provide product leadership. We believe that this study can contribute to exploring operational issues using MOL data in product life cycle engineering. In particular, providing methods as to how to define product degradation status and how to use it to other applications can be one contribution when considering its usability on other research areas. This study can be extended in multiple directions. One can make more elaborate definition on degradation and degradation mode. In addition, one can develop more reliable index to assess the degradation status by carefully exploring the feature of product degradation and proposing suitable indicators. In addition, one could develop the method for identifying the causes of product degradation based on product usage data and integrate the method with the DMCA approach.

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## Appendix. Estimating the remaining lifetime

### Notations

| | |
|---|---|
| $\Delta K$ | Stress intensity factor ($\Delta K = K_{\max} - K_{\min}$) |
| $K_{\max}$ | Maximum stress intensity |
| $K_{\min}$ | Minimum stress intensity |
| $F$ | The number of stress cycles |
| $\beta$ | Correction factor to the crack geometry and loading conditions |
| $\sigma$ | Stress |
| $\Delta\sigma$ | Stress level ($\Delta\sigma = \sigma_{\max} - \sigma_{\min}$) |
| $\sigma_{\max}$ | Maximum stress of cyclic load |
| $\sigma_{\min}$ | Minimum stress of cyclic load |
| $a$ | Crack length coefficient (depending on the crack geometry) |
| $a_t$ | Crack length coefficient at a certain time $t$ |
| $a_f$ | Critical crack length coefficient |
| $\dot{a}$ | Crack growth rate measured by the crack propagation sensor |
| $\Delta N$ | Remaining number of cycles |
| $C$ | Empirical parameter |
| $m$ | Empirical parameter |
| $T_L$ | Planned lifetime (in our case, 8000 h) |

Step 1. Collect usage status data of the heavy construction equipment vehicle at a certain time $t$.

We can gather operating time, stress levels ($\Delta\sigma$) of a structural part, the number of stress cycles ($F$), and crack propagation data ($\dot{a}$) from an embedded information device with sensors.

Step 2. Estimate remaining lifetime of the structural part at a certain time $t$.The following is the detailed procedure as to how to estimate the remaining lifetime of the structural part.

1. Find mission profile parameters ($\Delta\sigma$, $F$)Considering the future usage of the structural part, select suitable $\Delta\sigma$ and $F$ in the user model.
2. Calculate stress intensity factor ($\Delta K$)The values of mission profile parameters can be used as external load conditions to the different structure pins, which ensure the linkage between a structural system and other TTL parts (frame, bucket, and lateral cylinders). The external load conditions applied to an adequate CAD model can be used to make a finite element analysis (FEA) to find the stress profile history corresponding at the particular external loads, for each location of the structure. At a sensor measurement point, the FEA will provide a dynamic stress profile, which is called a *local stress profile*. This type of stress profile is difficult to use just as it is and needs to be transformed. The fracture mechanic theory (Dowling [20]) shows that the stress profile can be transformed in a new regular stress profile, which involves the same temporal degradation (crack growth) and has the same frequency ($F$). With the following equation, we calculate stress intensity factor. Here $a$ and β can be empirically determined from previous experience.

$$\Delta K = K_{\max} - K_{\min} = \beta \cdot \Delta\sigma \cdot \sqrt{\pi \cdot a} \tag{10}$$

where $K_{\max} = \beta \cdot \sigma_{\max} \cdot \sqrt{\pi \cdot a}$ and $K_{min} = \beta \cdot \sigma_{\min} \cdot \sqrt{\pi \cdot a}$

3. Select suitable $C$ and $m$ at Paris-Erdogan model (Monahan [21]) (Eq. (11)). Using fracture mechanics theory (Monahan [21]), we can know the relation between crack growth rate ($\dot{a}$) and stress intensity factor ($\Delta K$). The law relating crack propagation speed $\dot{a}$ to $\Delta K$ is derived from experimental results. The most widely accepted one for several materials is the Paris-Erdogan model.

$$\dot{a} \cong \frac{da}{dN} = C(\Delta K)^m \tag{11}$$

where $C$ and $m$ are empirical parameters determined by the fitting Eq. (11) to the fatigue data. Factors which affect crack propagation can be grouped into the following categories: material microstructure, processing, load spectrum, environment, and geometry of a component. In this study, we will consider only load spectrum, component geometry, and working environment for the crack propagation modeling and remaining lifetime prediction.

4. Calculate the remaining lifetime ($T^*$).Using the following equation, we can calculate the remaining lifetime of the structural part.

$$T_R(t) = T_L \cdot \frac{\Delta N}{F} \text{ where } \Delta N = \int_{a_t}^{a_f} \frac{1}{C \cdot (\Delta K)^m} da = \int_{a_t}^{a_f} \frac{1}{C \cdot (\beta \cdot \Delta\sigma)^m \cdot (\pi \cdot a)^{m-2}} da \tag{12}$$

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