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# Estimation of prospective states of mechanical parts for lifecycle support by part agents

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This paper discusses the lifecycle simulation of mechanical parts that are managed by part agents to promote their effective reuse.

It is essential to promote the reuse of mechanical parts with lifecycle management for the realization of a sustainable society. However, it is difficult to manage products in the use phase of product lifecycles owing to the unpredictable and uncontrollable behavior of consumers. This paper proposes a product lifecycle management system, called part agent system, using network agents and RFID tags attached on parts to promote reuse.

A part agent generates advice for the user regarding the maintenance of corresponding parts based on its current state and lifecycle information. The lifecycle simulation scheme performed by part agents is described herein. First, a part agent expands the part lifecycle with time. Next, it estimates by simulating the deterioration of the part and subsequently selects preferable maintenance actions. To simulate forthcoming states of the part, the possibility of events related to the part is estimated based on the causal relation of events with the acquired data on the states of the part, user operations, and detected events. Herein, a proposed method is presented to describe how the deterioration process is represented as causal relations with probabilities and how the relation is created using simulation. The simulation method is described for two example cases: fatigue of spring and deterioration of joints of a robotic manipulator.

**Keywords:** Part reuse, Part agent, Lifecycle simulation, Deterioration

## 1 Introduction

The effective reuse of mechanical parts is important for the development of a sustainable society [1]. To realize effective part reuse, it is essential to manage individual parts over their entire lifecycle because each individual part exhibits a different reuse history. However, it is difficult for manufacturers to predict such information owing to the uncontrollable and unpredictable diversity of user behavior. For users, specifically for consumers, it is difficult to access appropriate information for the maintenance of their parts. We propose a scheme whereby a part “manages” itself and supports user maintenance activities to address these issues [2].

We have proposed a scheme for a part agent to generate advice regarding the maintenance of corresponding parts [3]. We herein describe our proposed method to create a causal relation of events that may occur in a lifecycle stage. This causal relation is generated based on knowledge and simulation on deterioration and is used to calculate possibilities of transition between lifecycle stages.

A framework based on a part agent that estimates the prospective states of a corresponding part is described in section 2. In section 3, a proposed scheme to evaluate values of lifecycle stages and lifecycle paths in the near future using causal relations on deterioration is described. Simulations of deterioration of a spring and robotic manipulator are presented for evaluation in section 4. Section 5 summarizes the paper with remaining issues.

## **2 Estimation of prospective states for lifecycle support of parts**

A part agent manages all information regarding its corresponding part throughout its lifecycle. The proposal assumes the spread of networks and high-precision RFID (Radio-frequency Identification) technology [4]. A part agent is generated at the manufacturing phase of a core part, when an RFID tag is attached to its corresponding part. The part agent identifies the ID of the RFID tag during the part's lifecycle, tracking the part through the network. The part agent communicates with various functions within the network to collect the information needed to manage its corresponding part such as product design information, predicted deterioration of parts, and market information. It also communicates with local functions on-site, such as sensory functions that detect the state of the part and storage functions for individual part data.

Based on this scheme, a part agent creates advice for the user regarding the maintenance of the corresponding part [3]. This conceptual scheme is still in planned phase and contains many development issues but we expect it can be realized in the near future considering the current emerging technologies on digitalization including IoT and cyber-physical systems.

Challenges in promoting parts reuse include selection of parts to be replaced. The decision whether a certain part should be replaced is made based on the monitored state of the part and its diagnostics. Methodologies on condition-based maintenance and predictive maintenance of a product have been developed, such as those described in [5, 6]. In addition, to detect and diagnose the current situations of parts and products using these methods, it is advisable to consider their expected state by forecasting the forthcoming stages of the lifecycle. Users require assistance on deciding whether a part should be replaced and, in the case of a replacement, when and with which part it should be replaced.

Fig. 1 shows a framework for a part agent to advise its user based on the lifecycle model of a part. A lifecycle model consists of lifecycle stages and paths that represent the transfer between them. The stages are represented based on human actions related to the part, such as produce, sell, use, repair, and dispose. At each time step, the part agent predicts possible states of the part in the near future and evaluates the options of actions to provide advice to the user [7]. For the representation of life cycle model,

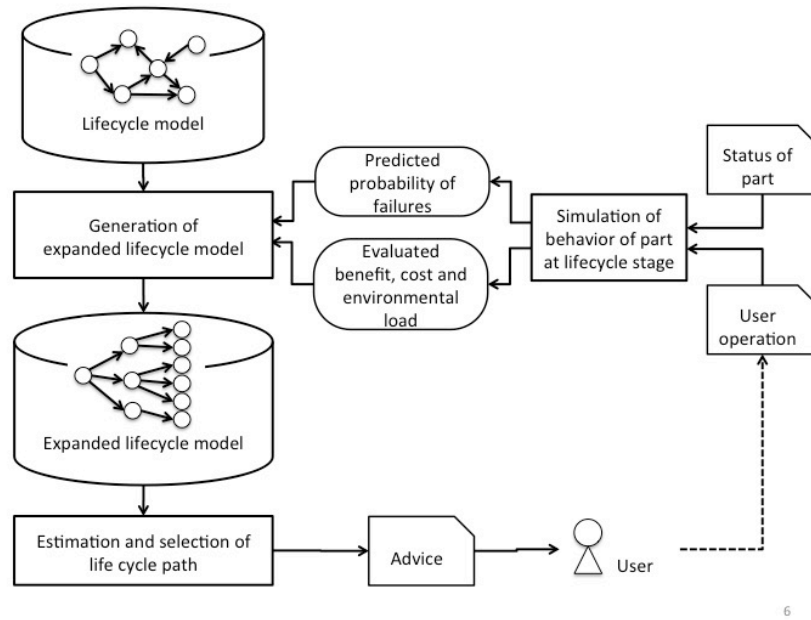


Fig. 1 Generation of advice by part agent

Wuest [8] used similar representation in his case studies where the state transfer of a product captures events in MOL (middle of life) of the product.

A part agent expands the lifecycle to evaluate every option of the expanded lifecycle path for several time steps in the future. Fig. 2 shows a simple example of the expanded lifecycle of the part starting from the “use” stage. Circles represent lifecycle stages and arrows depict lifecycle paths. An expanded lifecycle of the part represents possible actions in its lifecycle over time. For every time step, a part agent evaluates every action option in next step, i.e., “use,” “repair,” and “dispose” stages in the case of this figure, selects the best action, and advises the user with the result.

The evaluation of actions in the lifecycle is based on the simulated state of the part, including the estimations of its environmental load, benefit, and cost. These values are

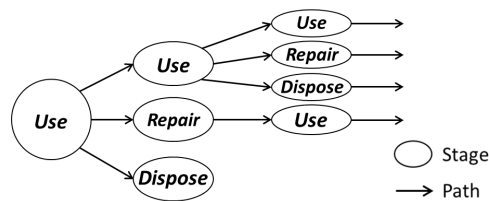


Fig. 2 Expanded lifecycle

estimated for every lifecycle stage in the near future. They can be estimated primarily based on the operations and usage performed in the stage, such as the load and duration of the task that the product achieves. The current status of the part, its deterioration, and the possibility of failures are considered in the estimation of the lifecycle stage. Probability is assigned to each expanded lifecycle path. It represents the probability of a part agent in taking that path and is estimated considering the probability of failures of the part.

Expected values such as environmental load, benefit, and cost for every option of the actions in the next step are calculated by accumulating the expected values of the forthcoming stages connected to the candidate stages. Each expected value is calculated as the product of the value in the stage and the possibility of the path connected to it [9].

### 3 Evaluation of prospective lifecycle stages and paths based on causal relations

As described above, values of lifecycle stages and possibilities of lifecycle paths must be evaluated to estimate the expected values of candidate stages. Hence, part deterioration is simulated as shown in Fig. 3.

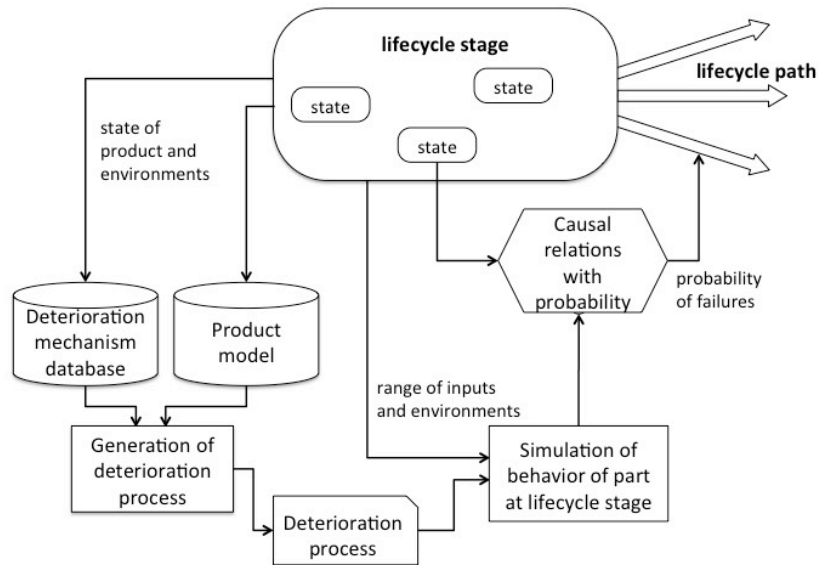


Fig. 3 Evaluation of lifecycle stage based on simulated deterioration

First, a deterioration process is constructed by combining deterioration mechanisms derived from a database or a library of deterioration mechanisms. A deterioration mechanism represents the deterioration that occurs when specific factors exist in the product

and environments. A mechanism may yield other factors that cause other mechanisms. Thus, a deterioration process is generated as a tree structure comprising multiple mechanisms combined by common factors [10]. This process qualitatively depicts the progress of deterioration under specific conditions.

Next, we simulate the deterioration mechanisms to evaluate the probabilities of their occurrences. It is performed by accepting the range of user inputs and environmental values such as the temperature during the stage. We assume that the deterioration database contains, as the information of each mechanism, a function to calculate the resultant deterioration value from the input factor values. The function may be either a simple function such as a spreadsheet, or a complex function such as dedicated simulation software. A threshold for the range of each input can be assigned depending on the application to discriminate whether a certain condition holds. For example, when the parameter of an input factor is a load value, a condition “heavy load” may be defined to indicate that the load is larger than, e.g., 100 kg. Similarly, a threshold can be assigned for the resultant deterioration value to determine whether the value is acceptable. For example, when the parameter of the resultant factor is a deviation, a condition “large deviation” may be defined to indicate that the deviation is larger than 1 mm. With these factor values of range and threshold, the simulation calculates the probability of occurrence of the resultant factor against the occurrence of the input factors. In other words, the simulation generates the conditional probability of a deterioration mechanism. For example, the simulation calculates the probability that “large deviation” occurs when “heavy load” exists and the probability when “heavy load” does not exist. Furthermore, it calculates the probability of “large deviation” not occurring when “heavy load” exists and when it does not exist. Examples of deterioration simulation are described in the next section.

As the conditional probabilities are assigned to every deterioration mechanism at the stage, the deterioration process can be regarded as a causal relation model among factors. As the range of input factors is provided at the stage, the probabilities of deterioration and failures can be estimated using this model. We can infer the probabilities of the lifecycle path from the stage using these probabilities because the stages “replace” and “dispose” are closely related to deterioration and failures.

Causal relations were used in SAPPhIRE model that was originally developed for design phase and was extended for MOL (middle of life) of the products [11]. While SAPPhIRE model intends to represent MOL events and activities in a generic way using ontology technology, our study aims to simulate the deterioration of products as described in the next section.

#### **4 Simulating deterioration using product model and deterioration model**

We describe two examples to demonstrate how the conditional probabilities for causal relations is estimated using deterioration simulations. The deterioration phenomenon of the first example is the fatigue of a spring and that of the next example is the deterioration of manipulator joints.

#### 4.1 Spring deterioration

In the first example, a simple steel spring is used. It is known that metals break under repeated stress. This phenomenon called fatigue occurs according to the stress and number of repetitions. The relation between magnitude of cyclic stress and number of cycles (in logarithmic scale) to failure can be represented by an S–N curve [12]. In other words, the deterioration mechanism of fatigue is represented by an S–N curve.

The conditional probabilities for spring deterioration that are calculated based on this curve using the Monte Carlo method are as follows. See Fig. 4 for the illustration of the method.

- (a) Input values and events: The input values for this deterioration mechanism are the magnitude of cyclic stress on the spring and its number of cycles. The input events are “high stress” for the magnitude of stress and “large number of cycles”

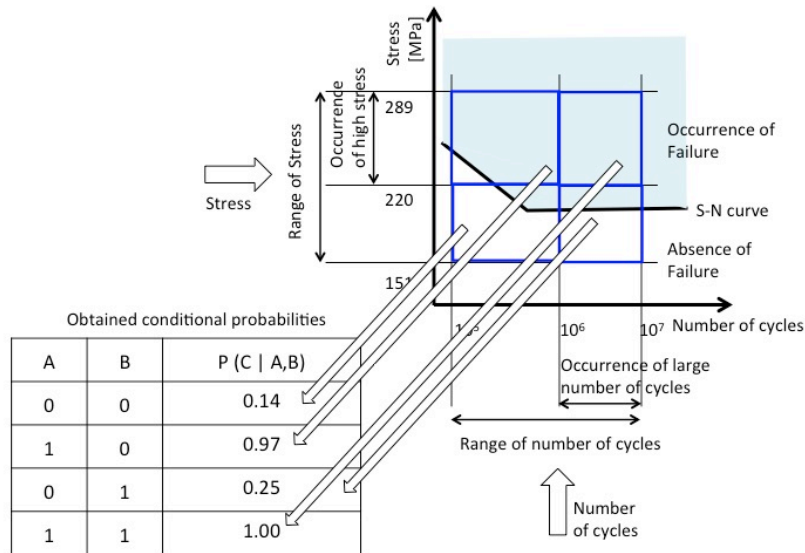


Fig. 4 Calculation of conditional probabilities for spring failure

for the number of cycles. The ranges of those values and the thresholds to determine the occurrence of the input event are presented as shown in the graph of Fig. 4. Sets of input values are generated randomly within their ranges. The input values should be generated following the actual distribution if available; however, they are distributed uniformly in this example.

- (b) Occurrence of spring failure: The occurrence of resultant event or spring failure is determined by comparing against the S–N curve. Failure occurs if the stress magnitude is larger than the value of the S–N curve for the number of cycles.



Here, we approximate an S–N curve comprising two line segments, as shown in the figure.

- (c) Conditional probabilities: For the combination of occurrence and absence of input events, i.e., whether high stress and a large number of cycles exists, probabilities of occurrence of resultant event or spring failures are calculated by adding the number of occurrences of failures against the number of input values that are generated randomly.

## 4.2 Deterioration of robot manipulator joint

Cases exist where the resultant occurrences exhibit more complex relationships with the input values. As an example, we developed a system to calculate the position error of the end effector of a manipulator with three degrees of freedom with a deteriorated joint.

- Simulation of robotic manipulator's behavior with deterioration of its joints

Fig. 5 shows the configuration of the system to simulate the kinematic behavior of a manipulator considering the deterioration of its joint. The operation of the manipulator and its environment are provided according to the situation of the lifecycle stage. The following are procedures to calculate the state of the manipulator.

1. First, simulate the behavior of the manipulator without the deterioration of joints using the nominal manipulator model and obtain loads on the joints.
2. Next, the deviations of joints are calculated based on the calculated loads using the deterioration model of the joints.
3. When the deviation of a joint is detected, the joint deviation model that provides transformation representing the deviation is associated to the nominal manipulator model.
4. Subsequently, the behavior of the manipulator is simulated again using a manipulator model with deviation in the joint to calculate the position error of the end effector.

- Kinematic model of a manipulator with deteriorated joint

The kinematic model of a manipulator is represented by a series of coordinate transformations [11]. Each transformation is a matrix of  $6 \times 6$  elements and represents either a rigid relation between two joints in a link or a variable relation between two links in a joint. For the manipulator with three degrees of freedom, i.e., with three joints, the matrix representing the position and orientation of the end-effector is as shown in equation (1).

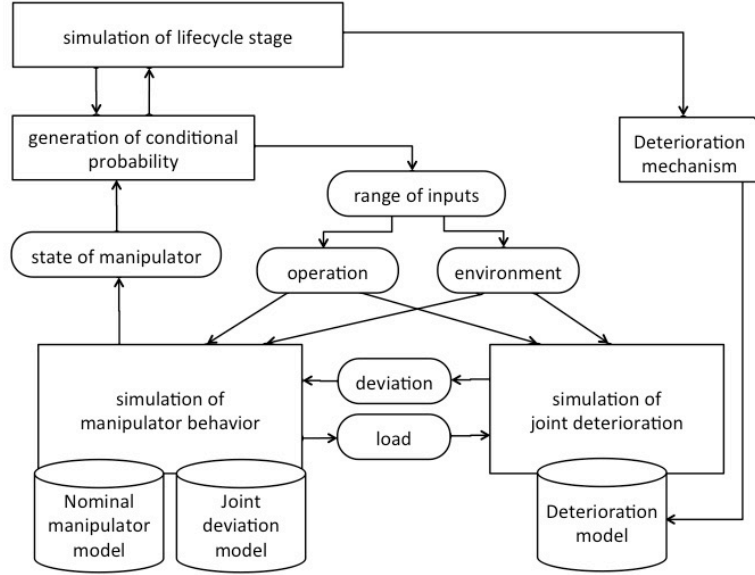


Fig. 5 Simulation of behavior of a manipulator with deterioration in its joints

$$T_E = T_{L0} T_{j1}(\theta_1) T_{L1} T_{j2}(\theta_2) T_{L2} T_{j3}(\theta_3), \quad (1)$$

where  $T_{Li}$  denotes the transformation between two joints in a link  $i$ ;  $T_{ji}(\theta_i)$  denotes the transformation between two links connected by a joint  $i$  with joint angle  $\theta_i$ .

When joint  $k$  exhibits translational deviation  $(\Delta x, \Delta y, \Delta z)$  and rotational deviation  $(\Delta \alpha, \Delta \beta, \Delta \gamma)$ , the transformation matrix  $T_{dk}$  representing this deviation is as follows [12]:

$$T_{dk} = \begin{pmatrix} 1 & -\Delta \gamma & \Delta \beta & \Delta x \\ -\Delta \gamma & 1 & -\Delta \alpha & \Delta y \\ -\Delta \beta & \Delta \alpha & 1 & \Delta z \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (2)$$

This transformation is inserted at the transformation of the joint to calculate the kinematics of the manipulator. For example, if joint 1 exhibits deviation  $T_{d1}$ , equation (1) becomes the following:

$$T_E = T_{L0} T_{d1} T_{j1}(\theta_1) T_{L1} T_{j2}(\theta_2) T_{L2} T_{j3}(\theta_3) \quad (3)$$

- Deterioration of a joint

We assume that the deterioration that causes joint deviation is caused by the force and torque applied to the joint. The following elastic relation exists between the deviation  $(\Delta x, \Delta y, \Delta z, \Delta \alpha, \Delta \beta, \Delta \gamma)$  and load  $(F_x, F_y, F_z, M_x, M_y, M_z)$ , where  $(F_x, F_y, F_z)$  is the force and  $(M_x, M_y, M_z)$  is the torque applied to the joint.

$$\begin{pmatrix} \Delta x \\ \Delta y \\ \Delta z \\ \Delta \alpha \\ \Delta \beta \\ \Delta \gamma \end{pmatrix} = K^{-1} \begin{pmatrix} F_x \\ F_y \\ F_z \\ M_x \\ M_y \\ M_z \end{pmatrix}, \quad (4)$$

where  $K^{-1}$  is a compliance matrix of the joint. For simplicity, we assume that the deterioration deviation is proportional to the accumulation of this elastic deviation.

If the position error of the end effector thus calculated is greater than the predefined threshold value, the occurrence of failure is identified. In other words, the proposed system serves as a function to determine the occurrence of failures similar to the S–N curve for the spring example described in 4.1. This example illustrates how causal relations can be created with probabilities for complex systems such as robotic manipulators by simulating deterioration.

## 5 Conclusion

A scheme for lifecycle simulation was proposed for a part agent to predict the prospective states of the corresponding part. The scheme generated a causal relation for a lifecycle stage based on the deterioration process. The probabilities of the causal relation were calculated using simulation and described herein. A simple case of a spring and a complex case of a robotic manipulator were explained.

Issues that remain necessitate the further development of the system. A detailed implementation of the system is yet to be completed and its applicability should be verified. As the causal relation involves conditional probabilities, Bayesian estimation is applicable to calculate the current probability of failures using this model. We are currently developing this functionality. The development of an appropriate deterioration model is also an important research issue.

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