Part agent that proposes replacement of a part considering its life cycle using a Bayesian network

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Abstract

Managing information on individual parts throughout their life cycle is a requisite to promoting their reuse. To do so, we have been developing a part agent system that uses network agents and RFID technology. A part agent proposes appropriate maintenance actions for a part based on information about its life cycle. This paper describes a method for a part agent to predict possible states of the corresponding part and to select an appropriate action by using a Bayesian network based on information collected on the state of the part, consumer preferences with regard to maintenance, and its usage.

1. Introduction

The effective reuse of mechanical parts is important for the development of a sustainable society [1]. To realize effective part reuse, managing individual parts over their entire life cycle is essential because each individual part has a different reuse history.

For reuse-based production, manufacturers need to capture the quantity and quality of the parts returned for reuse. However, it is difficult for manufacturers to predict such information because of the uncontrollable and unpredictable diversity of user behavior. On the other hand, it is difficult for product users to manage and carry out appropriate maintenance on the large number and variety of parts in the products they own.

Therefore, we propose a scheme whereby a part “manages” itself and supports user maintenance activities. For this purpose, we are developing a management system that includes network agents. Each agent is programmed to follow its real-life counterpart throughout its life cycle. We refer to this network agent as a “part agent” [2].

The part agent advises users on the reuse of parts and promotes the circulation of reused parts. Using this mechanism, consumers can also learn about environmentally friendly product uses and predicted product failures.

We previously proposed a framework of part agents [3] that advises the consumer on the ecologically responsible use of parts based on an evaluation of their possible states in the near future. In this paper, we introduce a part agent function to the framework that estimates the failure probability of the corresponding part by using a Bayesian network to represent the probabilistic causal relationships among the failures and user operations of the part.

To evaluate the effectiveness of the method, we developed a prototype function that evaluates reused parts for replacement by calculating their expected future cost based on their failure probability as estimated by the Bayesian network.

The concept of part agents is explained in section 2. The fundamental theory of Bayesian estimation is briefly introduced in section 3. The part agent function under development is described in section 4. The prototype simulation developed for evaluation of the Bayesian network is described with the results in section 5. Section 6 concludes the paper.
2. Conceptual scheme of part agent

A part agent manages all information about its corresponding part throughout its life cycle. The scheme assumes the spread of networks and high-precision RFID technology [4].

A part agent is generated at the manufacturing phase of core parts when an RFID tag is attached to its corresponding part. The part agent identifies the ID of the RFID tag during the part’s life cycle and tracks the part through the network. We used RFID tags as a method of identification because they have a higher resistance to smudges or discoloration than printed bar codes, which is important over long life cycles.

In related research, the product embedded identifier (PEID) [5] involves a small computing chip, an RFID tag, and sensors to support the middle and end of the product life. In contrast to the PEID system, our system aims to promote multiple reuses of individual parts that may go beyond the manufacturer’s management. This requires a “lightweight” system that can be used repeatedly without maintenance of sophisticated hardware.

Fig. 1 shows the conceptual scheme of the part agent. The part agent communicates with various functions within the network and collects the information needed to manage its corresponding part, such as product design information, the predicted deterioration, logistic information, and market information. It also communicates with local functions on-site, such as sensory functions that detect the state of the part, management and control functions of the product. Communication is established by using subordinate information agents generated by the part agents.

3. Estimation of part failure using Bayesian network

Predicting failure is an important function of a part agent to support the effective reuse of the part. However, doing so is difficult because of the probabilistic nature of failure and its dependency on the level of usage by the consumer and on the environmental conditions. To deal with this problem, we applied an estimation method based on a Bayesian network.

A Bayesian network is a directed acyclic graph that represents causal relationships among events with a conditional probability table for each event node. It is a probabilistic model that is used for predicting uncertain events, decision-making, and failure diagnostics. Node probabilities are calculated by giving information to observable nodes and by propagating probabilities via the network structure based on the conditional tables of the nodes [6].

Fig. 2 shows a simple example of a causal network with conditional probability tables. The graphic on the left side of the figure depicts the probabilities that events A and C affect event B. The probability of event B varying with the occurrence (shown as 0 and 1 in the table) of events A and C is called the conditional probability, and this is summarized in the conditional probability table on the right side of Fig. 2.

The probability that event A occurs after event B is obtained by Bayes’ theorem in equation (1):

\[
P(A|B) = \frac{P(B|A)P(A)}{P(B)}
\]

where \(P(A)\) is the prior probability of the occurrence of event A before event B and \(P(A|B)\) is the posterior probability of the occurrence of event A after event B has occurred. The probability of the occurrence of event A can be estimated when event B is known to have occurred based on the prior probability of event A, or \(P(A)\), and the conditional probability \(P(B|A)\).

We represent probabilistic causal relationships between part failures and their factors by using this Bayesian network in order to obtain the failure probabilities.

| A | C | P(B|A,C) |
|---|---|---------|
| 0 | 0 |  p11    |
| 0 | 1 |  p12    |
| 1 | 0 |  p13    |
| 1 | 1 |  p14    |

Fig. 2 Example of Bayesian network with conditional probability table.

4. Agent advice based on life cycle information using Bayesian network

In a previous paper [3], we proposed a basic framework for a part agent to advise a user based on the life cycle model of a part. At each time step, the part agent predicts possible states of the part in the near future and evaluates those options in order to advise the user.

A part agent expands the life cycle to evaluate each optional expanded life cycle path for several time steps in the future. The states of the part, including its environmental load, value, and cost, are estimated for every life cycle stage in the near future by using the current status of the part and information about its deterioration and failure.

In the previously proposed framework, models representing the deterioration, value, cost, and environmental load were simplified and not elaborated. We consider the deterioration model to be the most important as the
deterioration of a part is not only related to its failure but also affects its value, cost, and environmental load. Considering its probabilistic nature, we applied a Bayesian network for the deterioration model to relate part failure with the operational history of its user and the current status of the part, as shown in Fig. 3.

We expanded the life cycle of a part into a model with a tree structure. The expanded life cycle represents the possible changes in the life cycle of the part over time. An expanded life cycle path represents the transfer from an expanded life cycle stage to another stage in one time step. Each expanded stage requires or generates values for the time step, such as the cost, environmental load, and value. A probability is assigned to each expanded life cycle path to represent the estimated probability that the part agent takes that path. It is derived from the user preferences for maintenance and the failure probability of the part.

The deterioration of a part varies depending on the usage environment, such as the temperature, and the usage level, such as the frequency and intensity. However, the relationship between failure and these factors cannot be clearly quantified because of its probabilistic nature. To deal with this problem, we employed the Bayesian network described in section 3 to capture the causal effects of various factors on part failure.

Since failure is mainly affected by deterioration and user operation, we provide part agents with the capability of collecting sensory data on the status of a part and the user's operations. The prior probabilities of the Bayesian network are derived from the collected information.

In addition to the deterioration model, various models are required for the part agent to evaluate appropriate maintenance actions: a value model that represents changes to the value of the part; a cost model that represents the required cost of the part; an environmental load model that represents the environment load of the part; and a user model that represents the user behavior in relation to the part. Although these models are interrelated, they are mostly affected by the state of the part.

5. Prototype system of Bayesian estimation

5.1. Evaluation of reused parts based on Bayesian estimation

To evaluate the applicability of an estimation based on a Bayesian network, we developed a prototype system for part agents to generate advice on the evaluation of reused parts [7]. Taking a hard disk drive (HDD) as an example, the system estimates the expected profit a consumer gains when his current HDD is replaced with a candidate reused drive.

First, whether or not a reused part satisfies the consumer’s needs must be determined. We developed our system based on the concept shown in Fig. 4. The system estimates the part failure by using a Bayesian network to represent probabilistic causal relationships based on the state of the part and the user’s operations. Based on the estimated part failure, the cost is estimated, and appropriate maintenance actions by the consumer are proposed. Note that the conditional probabilities of the Bayesian network are estimated by using the results of periodic maintenance collected from multiple part agents.

5.2. Example with simple causality model

First, we tested the system for a simple mechanical part. The state of such a part varies according to the consumer’s operations and consequently may require maintenance. Its causal network is modeled in Fig. 5.

In the figure, the white boxes represent input events, the dark blue boxes represent observable events, the light blue boxes represent unobservable events, and the gray boxes represent target events for which the probability is yet to be estimated.

Assume that operations 1–3 represent the consumer’s operations and that states 1–2 represent the observable (using sensors) states of the part. Operations 1–3 affect the occurrences of defects 1 and 2. Defect 1 affects the occurrence of state 1, and defect 2 affects the occurrence of state 2. We assumed that costly maintenance is required when defect 2 occurs.
We calculated and compared the probabilities of maintenance for parts with the occurrence of states 1 and 2—i.e., $P(M|O_1)$ and $P(M|O_2)$—for consumers (users 1–8) with different prior probabilities with regard to operation. The probabilities took a minimum of 0.10 and maximum of 0.90, as shown in Table 1. The calculation was performed using the conditional probabilities in Fig. 6.

<table>
<thead>
<tr>
<th>User</th>
<th>$P(Op_1)$</th>
<th>$P(Op_2)$</th>
<th>$P(Op_3)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>User 1</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>User 2</td>
<td>0.10</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td>User 3</td>
<td>0.10</td>
<td>0.90</td>
<td>0.10</td>
</tr>
<tr>
<td>User 4</td>
<td>0.10</td>
<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
<td>User 5</td>
<td>0.90</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>User 6</td>
<td>0.90</td>
<td>0.10</td>
<td>0.90</td>
</tr>
<tr>
<td>User 7</td>
<td>0.90</td>
<td>0.90</td>
<td>0.10</td>
</tr>
<tr>
<td>User 8</td>
<td>0.90</td>
<td>0.90</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Fig. 7 shows the calculation results of $P(M|O_1)$, $P(M|O_2)$, and $P(M)$ for each user. $P(M|O_1)$ was lower for users 1, 2, 4, and 6, and $P(M|O_2)$ was lower for users 3, 5, 7, and 8. This means that, when we have a reused part A in state 1 and a reused part B in state 2, the probability of the need for repair is low if users 1, 2, 4, and 6 use part A and users 3, 5, 7, and 8 use part B.

The probability of defect occurrence varies depending on the combination of the consumer’s usage levels and state of the part. As shown in the example above, the Bayesian network can be used to estimate the appropriate combination of the consumer and part.

5.3. Derivation of conditional probability by part agent

Conditional probabilities, such as those in Fig. 6, are required in advance to estimate the probability of defect occurrences. Thus, we considered deriving the conditional probability from a periodic inspection of parts to detect defects that are undetectable during operation. A simple way to obtain the conditional probability is to calculate the rate that a conditioned event occurs for all occurrences of the event. However, when the probability of the event’s occurrence is low, it is difficult to calculate the probability from the data of one part. Therefore, the part agent calculates the conditional probability based on data collected from other part agents on the same part used by different users.

To evaluate the scheme, we simulated the occurrence of events with the probabilities shown in Fig. 6 and calculated the conditional probability from data on the event occurrence for every periodic inspection. Fig. 8 shows the conditional probabilities obtained from a part used by one consumer. Fig. 9 shows the results based on data collected from three consumers.

The correct conditional probability was not derived from the data of a single part as data were not available for events with a low probability. In contrast, when the data were collected from multiple parts, the calculation result was confirmed to converge to the conditional probability given in Fig. 6. If multiple part agents cooperate to revise the conditional probability at each periodic inspection, the probability can be more accurately estimated.
5.4. Simulation of HDD

A part agent evaluates reused parts based on the estimated probabilities to propose maintenance actions for the part. A simulation was performed to evaluate the number of produced parts and the costs that every consumer has to bear. Note that the part agent does not predict the future; electronic tags were not considered in the simulation.

5.4.1. Life cycle simulation

We defined the life cycle stages of a part as Production, Market, User, Maintenance, and Disposal.

- Production: A part is produced in this stage at the request of Market and sent to Market.
- Market: The part is sold and purchased in this stage. Production sends orders to Market to keep a constant number of parts in storage. The price of a new part was defined as 10,000 JPY. When User sells a part, Market pays User a reduced amount of money from the original price and sells the purchased part as a reused part. A tally is kept of the number of times the part is reused, and its price is decreased 2000 JPY every time it reaches Market as a reused part.
- User: The part is used in this stage. User requests maintenance when required. When the part fails, User buys an alternative. Based on the state of part, a decision is made on whether a part requires maintenance, and, if a part fails, whether it can be fixed.
- Maintenance: The part is fixed in this stage. Once fixed, the part gains the same state as that of a new part. When User asks for maintenance of a part, Maintenance fixes the part and sends it back to User.
- Disposal: The part is discarded in this stage. The corresponding part agent is also deleted.

The part agent calculates the expected cost when such events occur. It proposes maintenance if the condition in equation (2) holds and lets the part continue to be used otherwise. In the equation, $P_f$ denotes the probability for failure to occur, and $\overline{P_f}$ denotes the probability for it to not occur. $Cost$ represents the repair cost when a failure occurs, and $Profit$ represents the profit gained when no failure occurs. The part agent compares the difference between the expected cost and profit with $Cost'$, which is the cost required to replace the part with an alternative.

$$Cost \times P_f - Profit \times \overline{P_f} > Cost' \tag{2}$$

The simulation included every stage in the life cycle and multiple Users. Every User purchased a part from Market, and Market ordered parts from Production to maintain its stock. Parts were used by Users. They were sold to Market and exchanged with newly purchased parts according to the advice of the part agent. When a part failed or required maintenance, it was sent to Disposal or Maintenance, respectively.

The simulation started with new parts. After a specific time passed, the simulation output a number of new parts produced in Production and costs for every User.

5.4.2. Causal network model of HDD

Taking HDD as an example, the simulation was performed by creating a causal network model based on S.M.A.R.T. (Self-Monitoring, Analysis, and Reporting Technology) [8]. S.M.A.R.T. is a function installed in HDDs to predict their failures. It cannot predict all failures but is effective at detecting age deterioration in a stable environment. In S.M.A.R.T., the events scan errors, reallocation count, offline scan uncorrectable sector count, and current pending sector count are known to show a significant correlation with HDD failure [9].

Fig. 10 shows a causal graph model for the HDD. Events follow the same color scheme used in Fig. 5.

![Causal relations on HDD failure](image-url)
5.4.3 Simulation results

The simulation was performed under the following three conditions:

A) No advice by the part agent: User uses the part until a failure occurs, after which the part is discarded and replaced by a new part.

B) Advice from part agent.

C) Advice without calculation of failure probability. The advice is given according to a fixed probability of \( P_f = 0.1 \).

Note that the consumer follows the advice from the part agent.

For each condition, the simulation was performed for a specific duration of time. The accumulated cost that each User had to pay, the time duration that the part was used, and the number of produced parts at the end of the simulation were compared. Prior probabilities of each User are listed in Table 2.

Fig. 11 shows the rate of the cost against the operational time of the part for each User after 2000 steps.

For most Users, the cost was low when they received advice from the part agent. User 8 was assumed to incur a higher cost with the advice because all of its prior probabilities were 0.9. This means a high probability of failure and replacement with a new part, which would result in a short operational time and high cost. In this situation, we determined that using the part until its breakdown would cost less than replacing it earlier based on advice from the part agent.

The number of produced parts decreased with the advice of the part agents. However, the fewest parts were produced when the advice was made according to a fixed probability.

This may be because the frequent replacements resulted in a short operational time, which led to few parts being produced.

Appropriate maintenance by users following the advice of part agents would reduce the cost and number of the produced parts. We consider this scheme to be more effective when the cost of failure is far larger than the operational profit.

6. Conclusion

We proposed a part agent function based on a Bayesian estimate to advise the consumer on the ecologically responsible use of parts. To evaluate the effectiveness of the method, we simulated a prototype system of a part agent that evaluates reused parts for replacement by calculating their expected future cost based on their failure probability as estimated by a Bayesian network. This method can be applied to situations in the life cycle of a part to provide the consumer with appropriate maintenance actions.

Future work will involve integrating the Bayesian estimation and expansion of the life cycle. In addition, as most products are composed of multiple parts, part agents should be able to deal with assemblies.

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References


