Bayesian Networks-based association rules and knowledge reuse in maintenance decision-making of Industrial Product-service Systems

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Abstract

Equipment manufacturing firms nowadays increasingly provide Industrial Product-Service Systems (IPS2) to improve productivity and service capacity, particularly in the current age of big data. Vast amounts of data are collected using database management systems from areas of product design, manufacturing, marketing, fault detection and maintenance service of IPS2. An urgent challenge in context of IPS2 is how to form reusable knowledge taking advantage of these data records for the sake of guiding subsequent maintenance decision-making. To handle this issue, data mining technology has been used in knowledge acquisition from different databases. However, it needs further investigation on how to represent and reuse knowledge mining from these databases in IPS2 in relation to maintenance decision-making. Given this observation, this study first presents association rules in the form of Bayesian Networks that are mined from different databases of IPS2 and can be used to represent knowledge acquired. It then establishes a knowledge reuse framework based on Bayesian inference, which is used to support related decision-making in maintenance operations. Lastly, the proposed methodology is applied to a real-world case in an agricultural equipment manufacturing enterprise. The experimental results using real-time data sets illustrate the effectiveness of the proposed methodology in handling maintenance decision-making associated with related fault phenomena.

Keywords: Association rules; Bayesian network; Maintenance decision-making

1. Introduction

Association rules of events/nodes can be regarded as probability rules due to their co-occurrence [1]. Equipment manufacturing firms usually use association rules, which are mined from databases from areas of product design, manufacturing, fault detection and maintenance service of IPS2 with data mining technology, to seek the relation between the fault phenomenon and the fault treatment. Such relation is useful to support related decision-making in maintenance operations. However, it’s difficult and expensive to generate knowledge from document resources [2]. Since that, many researches focus on applying data mining technology to assist equipment operation and maintenance.

Data mining is known to be an excellent tool which helps the decision makers to discover the hidden knowledge and patterns when dealing with a large amount of data [3]. During the last decades, different methods of data mining technology have been used in various industries to find the tacit knowledge. According to the mode of the extracted knowledge, data mining tasks can be subdivided into: classification, clustering, association rules, prediction, and sequence mining, etc [4-6]. Association rules mining is part of the data mining methods. And up to now, there have been several tools of association rules mining, such as SPMF and WEKA, which use the algorithms such as Apriori and Fp-growth to find and generate association rules from database. Maintenance is known as a field where a great mass of data is daily collected [7]. So in the field of operation and maintenance, people applied this technology to discover the relation between the variation of the parameter and the different faults [8]. Paula Potes Ruiz and Bernaerd Kausu Foguem established a framework to manage and generate the knowledge mined from the maintenance data, by using association rules mining, to support the decision-making [9]. Baohui Jia find out different kinds of influence between different fault phenomena by using the association rules mining [10].
Bayesian network was defined explicitly by Pearl in 1988, and nowadays is one of the most effective theoretical models in the field of representing uncertain knowledge and reasoning [11]. It’s widely utilized in industry, such as fault diagnosis, fault prediction, military decision-making, information fusion, data mining based on probabilistic causal relationship, etc[12]. The application of Bayesian network in the field of fault diagnosis can be seen as a kind of diagnosis decision inference model, and it can be used in three aspects: fault classification, decision-making and fault prediction.

From these studies we can know that there are two questions for the applications of the association rules, which are:

(i) It’s difficult to use the discrete rules. Several studies show how to generate association rules or knowledge of maintenance from the database and store in database, but the representing of these rules is discrete and can’t express the relationship between rules. And it’s challenging to use the association rules properly when the number of association rules increases greatly. Moreover, how to maintain and reuse the discrete rules database is also a problem.

(ii) It’s complex to construct the Bayesian network based on the dataset. This method needs to traverse the entire dataset many times and its’ search space is large. The flexibility is poor and it can’t adapt to the dynamic data well.

In that context, this paper combines association rules with Bayesian network technology, and suggests a usual approach for generating the association rules mining with the tool SPMF, by storing association rules in the form of Bayesian Networks, and establishing a knowledge-reusing framework based on the Bayesian inference. In this way, the relationship of association rules can be expressed well by a Bayesian network. Moreover, it’s more convenient to utilize the association rules.

The rest of the article is organized as follows: In section 2, we describe the problem. Section 3 introduces the presentation method of association rules with the Bayesian network and suggests a reuse framework of association rules. Section 4 presents an illustrative example based on actual data dealing with the maintenance of agricultural machinery.

2. Problem statement

In this paper, we consider a real-world situation where the manager takes decisions for the maintenance service of IPS² by utilizing maintenance experience to improve the service capacity and efficiency. It is founded in China’s agriculture equipment manufacturing where decision-making of maintenance service is serious and urgent to be dealt with.

Agricultural equipment manufacturing enterprises provide parts and maintenance service to customers. In consideration of the influence of maintenance service, usually the manager will try to improve the evaluation from his clients. To enhance maintenance service capacity and efficiency, the staff in maintenance service center should try to provide the consumers or the maintenance engineer with maintenance suggestions quickly to solve the fault when they receive a maintenance task. However, only the experts have the skill response quickly for the fault treatment. And it’s impractical to employ various experts in the maintenance service centers. In such situation, it’s urgent to add the function for decision-making in the service system.

In fact, agricultural equipment manufacturing enterprises have accumulated a large amount of maintenance data, which contains so much hidden knowledge about the maintenance service. And we want to generate knowledge from the maintenance data to assist the decision-making in maintenance service. Because the number of maintenance data is large. Moreover, it contains the closed relationships between data, for example: fault phenomenon → fault solution. These relationships are so helpful for the decision-making. Therefore we advocated a model of using knowledge to assist the decision-making of maintenance service.

We study the model consisting of three parts: knowledge acquisition from maintenance experience, knowledge representing and knowledge application in maintenance service. Considering the features of maintenance data, we choose the association rule mining technology of data mining technology to acquire the rules, we then represent the association rule with the Bayesian network, and finally we utilize the rule network to assist the decision-making.

3. Methodology

3.1 Generation of association rule

3.1.1 Definition of an association rule

Association rule is one of the results of data mining, which can describe the relationship among things. It has two attributes: support and confidence. Assuming that x and y is two item sets, and X ∩ Y = ∅, so we can call X → Y association rules. The rule is established on the condition that it meets the requirement of support and confidence, which are determined by the user. The support of the association rule is the proportion of transactions in the database that contains both X and Y, and the frequency of the occurrence of the rule is as follows (Eq.(1)).

\[
\text{support} = \frac{\text{number of transactions containing both } X \text{ and } Y}{\text{total number of transactions}} \quad (1)
\]

The confidence of the association rule is determined by the percentage of transactions in the database containing X that also contains Y (Eq.(2)).

\[
\text{confidence} = \frac{\text{number of transactions containing both } X \text{ and } Y}{\text{number of transactions containing } X} \quad (2)
\]

3.1.2 Mining of the association rule

Mining of association rule mainly contains two tasks: the one is to find the frequent item sets which meet the support in data source; and the other one is to generate association rule between item sets according to the confidence. Obviously the core of the mining process is to find the frequent item sets. So the difference of several algorithms mainly focuses on the optimizing of finding the frequent item sets.
Now people have discovered several proper algorithms for mining association rules, such as the Apriori algorithm, Fp-growth algorithm, ECLAT algorithm, etc. And the Apriori algorithm is the most commonly used. The first step of the algorithm is to generate the frequent item sets. Because only need the association rules with two item sets in the structure of a Bayesian network, we modified the Apriori algorithm, and only generated 2-itemsets. The specific process as follows\cite{13}:

(i) The first iteration of the algorithm counts item occurrences to determine the large 1-itemsets \((L_1)\).

(ii) The following iteration is to generate the candidate item sets \(C_2\) according to \(L_1\), using the Apriori-gen function, which includes two union taking as \(L_1\) : union and pruning. In the union phase, all 2-itemsets candidates are generated. Then, in the pruning phase, all candidates generated in the union phase with some non-frequent 1-itemsets are removed.

The second step of the algorithm is to identify strong association rules. In this step, we need to find all association rules by traversing the frequent item sets. Then get the strong association rules based on the minimum degree of confidence.

3.2 The construction of Bayesian Network

3.2.1 Structure learning of Bayesian Network

Bayesian network is a directed acyclic graph, in which each node corresponds to a random variable and each directed edge represents the dependency between two nodes. And the antecedent and consequent of the association rule also has the dependency. So we use a Bayesian network to represent the relation of the association rule.

After the generation of the association rule in section 3.1, we generated the structure of Bayesian network as follows:

- The definition of Bayesian network is \(B = \{G, P\} = \{V, E, P\}\), in which \(G\) represents the directed acyclic graph, especially \(V\) represents a collection of nodes, \(E\) is collection of directed edge, and \(P\) is the collection of probability about the edge (the learning method will be illustrated in next section).

Input: association rule \(x \rightarrow y\)
Output: rule base
(i) Generate Graph \(G(V, E); V=\emptyset; E=\emptyset\);
(ii) For each node \(x\) and \(y\), if \(x \not\in V\), then \(V=V \cup \{x\}\); if \(y \not\in V\), then \(V=V \cup \{y\}\);
(iii) \(E= E \cup \{xy\}\);

3.2.2 Parameter learning of Bayesian network

After learning the structure of the Bayesian network, the next step is to learn the parameter of Bayesian network. There are two important parameters for the Bayesian network: the joint probability and conditional probability. Joint probability refers to the probability of two events occurring together. And conditional probability indicates the probability that an event will occur given that one or more other events have occurred.

Comparing the two parameters of the Bayesian network with the two attributes of association rule in 3.1.1, we can know that the joint probability of two nodes in Bayesian network is the support of the rule which consists of the two nodes, for example: \(p(A=1, B=1) = \text{support}(A \rightarrow B)\). And the conditional probability of two nodes is the confidence of the rule, for example: \(p(A=1|B=1) = \text{confidence}(A \rightarrow B)\). So in the process of parameter learning of Bayesian network, only is required record the support and confidence of the rules.

3.3 The proposed framework

Knowledge and experience management both include steps of collection, modeling, storage, evaluation and maintenance \cite{14}. In this section, a knowledge reuse framework was proposed to help decision-making with the association rules. The framework has three parts: rules matching, rules evaluation and solution determining.

3.3.1 Rules matching—Bayesian reasoning

According to the decision-making model of Bayesian network, system should have the quick reasoning ability. When the value of some node is gotten, system can quickly get the posterior probability of related rules.

Rules matching is the decision-making process of the Bayesian network. Decision-maker should find the most proper rules based on the Bayesian network. The entire decision-making process is shown in Fig. 1.

1) Simplified Bayesian Network

Because of numbers of rules, the scale of the Bayesian network is large, and it’s hard to get the proper solutions based on the priori conditions. In section 3.1, we have assumed conditional independence. So we can find the nodes related to the priori conditions, simplify the large Bayesian network and not change the probability. In this way, it can increase the efficiency of decision-making.

For example, in the Bayesian network \(N\) (as shown in Fig.2), we find the fault solution nodes \(B_1\) and \(B_2\) according to fault information \(A_\odot\), and need to calculate the posterior probability \(P_{N'}(B_1 | A_2)\) and \(P_{N'}(B_2 | A_2)\) in the Bayesian network \(N\) to compare the two solutions. In order to calculate the posterior probability simply and conveniently, we compute the \(P_{N'}(B_1 | A_2)\) and \(P_{N'}(B_2 | A_2)\) in Simplified Bayesian network \(N'\) (as shown in Fig.3) instead of \(P_{N'}(B_1 | A_2)\) and \(P_{N'}(B_2 | A_2)\) on the condition that \(P_{N'}(B_1 | A_2)\) equals to \(P_{N'}(B_1 | A_2)\) and \(P_{N'}(B_2 | A_2)\) equals to \(P_{N'}(B_2 | A_2)\). Finding the Simplified Bayesian network follows the principle: the minimum closed set of the ancestor nodes. It means that Simplified Bayesian network should contain all nodes related to \(A_2\) and their ancestor nodes. The specific search process is as follows:

Find all child nodes of \(A_\odot\{ B_1, B_2 \};\)
So B₁ and B₂. The specific calculation method is as follows:

Table 1. Probability table

<table>
<thead>
<tr>
<th>A₁</th>
<th>A₂</th>
<th>P(B=1)</th>
<th>P(B=0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0.86</td>
<td>0.14</td>
</tr>
</tbody>
</table>

From the Probability tables the computing method can be simplified as follows:

If Q is the node of certain Bayesian network, Parent (Q) represents the collection of the precursor nodes of Q, then:

\[ P(Q=0|\text{Parent}(Q)) = \prod_{i} p(Q=0|P_{i}) \] (3)

\[ P \in \text{parent}(Q) \text{ and } P_{i} = 1 \] From the definition of confidence of the association rule we can know that \( P(Q=1|P_{i}=1) \) equals to the confidence \( (P_{i} \rightarrow Q) \)[15]. So:

\[ P(Q=0|\text{parent}(Q)) = \prod_{i} (1 - \text{confidence}(P_{i} \rightarrow Q)) \] (4)

\[ P(Q=1|\text{parent}(Q)) = 1 - P(Q=0|\text{parent}(Q)) \] (5)

### 3.3.2 Rules evaluation

The evaluation of the rules for the user to accept the rules has great significance after getting the possible solutions and probability. This process can help users to find the proper solutions according to the specific status of the maintenance task. The usual method to evaluate rules is the subjective evaluation. This method is to evaluate the rules using the user experience. Experienced users point out the main limiting conditions of the maintenance task, such as the maintenance costs, environment, weather and so on. And determine the weight of each factor.

After getting the feasible solutions and probability, we generally select the rule with the largest probability as the best solutions. However, some maintenance tasks have some limiting condition, such as the maintenance costs, environment, weather and so on. So the best solution should be determined not only by the probability but also by the limiting conditions.

### 3.3.3 Solution determining

After the rule evaluation, we should calculate the maintenance efficiency of each fault solution based on the limiting condition, and determine the best solution according to the maintenance efficiency. In this paper, we think that the main factor is the maintenance cost to influence the solution. So we obtain the formula of the maintenance efficiency based on the maintenance cost. And the computing formula is shown as shown follows [16]:

\[ \text{eff}(B_{i}) = \frac{p(B_{i}=\text{true})}{c_{i}} \approx \frac{P_{i}}{C_{i}} \] (6)

In the equation: \( \text{eff}(B_{i}) \) represents the maintenance efficiency of the fault solution \( B_{i} \); \( c_{i} \) represents the maintenance cost of the fault solution \( B_{i} \); \( P_{i} \) is the probability of the fault solution \( B_{i} \) occurring.

Then we select the solution with the highest maintenance efficiency as the best solution.

### 4. Experiment result and discussion

In this section, Bayesian network is utilized to represent the association rules mining from the maintenance data and the knowledge reuse framework is used to support the maintenance decide-making in Chinese agriculture equipment manufacturing. We will describe the experimental data and the whole application process. Moreover, we select a random
failure phenomenon as a validation. Results of best fault solution will be given and analyzed.

4.1 Experiment data and basic steps

In this paper, the data come from a particular company’s maintenance data. In total, there are about 1000 transactions and 30 properties, such as serial number, maintainer, market, the serial number of fault reason, etc. Usually leading to the fault can be described by several variables, such as geographic information, fault component, fault phenomenon, etc. Concerning this, we select related properties from 30 properties as the mined data. Part of maintenance data is shown in Table 2.

<table>
<thead>
<tr>
<th>Fault phenomenon</th>
<th>Market</th>
<th>Sales time</th>
<th>Maintenance fault date</th>
<th>Fault source</th>
<th>Fault phenomenon</th>
<th>Fault solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grain dirty</td>
<td>Wannan market</td>
<td>2012/5/13</td>
<td>2012/6/1</td>
<td>Gearbox</td>
<td>adjust wind speed</td>
<td></td>
</tr>
<tr>
<td>Roller abnormal</td>
<td>North of Luxi market 2012/5/21</td>
<td>2012/6/5</td>
<td>roller XM0602057222</td>
<td>change</td>
<td>change roller</td>
<td></td>
</tr>
<tr>
<td>Indicator fault</td>
<td>North of Luxi market 2012/5/30</td>
<td>2012/6/2</td>
<td>indicator SD0602034002</td>
<td>change</td>
<td>change indicator</td>
<td></td>
</tr>
</tbody>
</table>

(1) Representing association rules

During the implementation process of rule mining, we select the Apriori algorithm in SPMF and WEKA which are open source program packages to complete our functions. We determined that the minimum support is 0.03, and the minimum confidence is 0.4. Then we selected the valuable rules as the knowledge which we require. And the results are shown in Table 3.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Result</th>
<th>Support</th>
<th>Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market=Wannan market</td>
<td>Fault solution=adjust wind speed</td>
<td>0.042</td>
<td>0.34687</td>
</tr>
<tr>
<td>Market=Wannan market</td>
<td>Fault solution=change indicator</td>
<td>0.062</td>
<td>0.34783</td>
</tr>
<tr>
<td>Market=Wannan market</td>
<td>Fault solution=adjust wind speed</td>
<td>0.036</td>
<td>0.42754</td>
</tr>
<tr>
<td>Market=Wannan market</td>
<td>Fault solution=adjust wind speed</td>
<td>0.038</td>
<td>0.33058</td>
</tr>
<tr>
<td>Market=North of Luxi market</td>
<td>Fault solution=change brake</td>
<td>0.062</td>
<td>0.3375</td>
</tr>
<tr>
<td>Market=South of Luxi market</td>
<td>Fault solution=change brake</td>
<td>0.083</td>
<td>0.41506</td>
</tr>
<tr>
<td>Fault phenomenon=grain dirty</td>
<td>Fault solution=maintain cap</td>
<td>0.034</td>
<td>0.38202</td>
</tr>
<tr>
<td>Fault phenomenon=grain dirty</td>
<td>Fault solution=change indicator</td>
<td>0.042</td>
<td>0.68</td>
</tr>
<tr>
<td>Fault phenomenon=Roller abnormal</td>
<td>Fault solution=change roller</td>
<td>0.046</td>
<td>0.4012</td>
</tr>
<tr>
<td>Fault phenomenon=Indicator fault</td>
<td>Fault solution=change indicator</td>
<td>0.048</td>
<td>0.44094</td>
</tr>
<tr>
<td>Fault part=Gearbox</td>
<td>Fault solution=maintain cap</td>
<td>0.056</td>
<td>0.34591</td>
</tr>
</tbody>
</table>

In order to make the Bayesian network more concise, we use the symbol A_i and B_j to represent the condition and result of the rules respectively, for example: A_1 represents the first condition Market=Wannan market; B_j represents the result Fault solution=adjust wind speed.

According to our representing method—the construction algorithm of Bayesian network, we construct the Bayesian network of maintenance knowledge. The Network of association rules is shown in Fig. 5.

(2) Reuse of association rules

After representing the association rules with Bayesian network, we can use it to assist the maintenance decision-making as knowledge based on history experience. We choose a maintenance task randomly as an application case. For example, there is a maintenance task in North of Luxi market, and the fault phenomenon of an agricultural machinery is grain dirty. Then depending to the basic fault information and the method of finding the simplified Bayesian network, the system can get the simplified Bayesian network (Fig.6) from the original Network.

From the fault description of the agricultural machinery, we know that both A_2 and A_4 are true. According to the reasoning method, we can get the probability tables of the nodes of fault solution as shown in Table 4.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>B_1</th>
<th>B_2</th>
<th>B_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability</td>
<td>0.65</td>
<td>0.33</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Assume that: the maintenance cost of B_1 is ¥100, the cost of B_2 is ¥50, the cost of B_3 is ¥80. And if we carry out the three solutions respectively, the operating efficiency of every fault solution is computed according to the method in rules evaluation. The operating efficiency is given in Table 5.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>B_1</th>
<th>B_2</th>
<th>B_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency</td>
<td>0.65%</td>
<td>0.66%</td>
<td>0.85%</td>
</tr>
</tbody>
</table>

4.2 Result analysis and discussion

Table 4 shows the maintenance solution reasoned by the Bayesian Network of association rules. Depending on the
probability, we know the fault solution labeled $B_4$ is the best solution, and the solution labeled $B_2$ is the worst one. Table 5 shows the maintenance solution and maintenance efficiency after rules evolution considering the separate maintenance cost. In such condition, the fault solution labeled $B_4$ also has the highest maintenance efficiency contrasting with the other two fault solutions. So we know that with the limitation of maintenance cost, carrying out the fault solution labeled $B_4$, namely changing rollers, is the best solution for this maintenance task. So the results provide maintenance managers with a solution when they receive a task, which is more reliable than they give a treatment without any knowledge supporting from history experience. However, we can see the fault solution $B_3$ is the worst one. So the rule evaluation has great influence on the selecting of the best fault solution. Unfortunately, we only consider the maintenance cost on the process of rules evaluation in this paper. Usually a maintenance task is influenced by several factors. So the influence from various factors should be considered and then we choose the fault solution with the highest efficiency as the optimal solution. In addition, we only consider two layers structure of Bayesian network. There is too little known about the computing method of the multi-layer structure of Bayesian network. So we decide to leave the questions open for future investigations.

5. Conclusion

In this paper, we have considered the knowledge discovering from the maintenance experience and reusing in the field of the maintenance service. It’s easy to mine knowledge from the history maintenance data with data mining technology, so this problem poses two challenges: How to represent the knowledge in the system and give a knowledge reuse framework for the maintenance service decision. We give the algorithm of the rule mining and construction of Bayesian network and we showed that, representing the association rules with Bayesian network is intuitional and simple. At the same time, it’s convenient to apply the rules later. In the representing of Bayesian network case, we provide a knowledge reusing model for the decision-making of maintenance service, which includes the rules matching, rules evaluation and the solution determining. The result of application example illustrates the feasibility of the representing method and shows that the proposed knowledge reuse framework can help the maintenance manager improve the efficiency of decision-making. Future work will include the reasoning of Bayesian Network from more than two layers structure, rules evaluation from various factors and improving the knowledge reusing framework for applying in multiple fields.

Acknowledgements

This research is supported by the National High-Tech. R&D Program, China (Project No. 2013AA040402). We express our sincere thanks to the Lovol International Heavy Industry Co., Ltd.

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