A PROBABILITY-REACTIVE ORDER PROCESSING METHOD BASED ON THE LOAD-ORIENTED ORDER RELEASE (LOOR) FOR MAINTENANCE OF CAPITAL-INTENSIVE GOODS

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The maintenance of complex capital goods wins more and more in importance. This article will describe a method to raise a condition prognostication of modules and spare parts and the corresponding order probabilities of spare parts during the tear down process. It will give an overview how uncertainty can be represented by the use of probabilities. The consideration of different factors of influence, for example external effects such as the operation period of a product, causal relationships and influence of damaged spare parts, can be represented by the use of Bayesian Networks.

1. INTRODUCTION

Maintenance processes are known in practice as so-called "MRO processes" (MRO - Maintenance, Repair and Overhaul). The customer-supplier relations are indicated by the demand for short downtimes and a high schedulability of the maintenance of the capital goods [1].

Low reaction time and process stability of the supplier can be measured by the customer on logistic target figures like delivery time and delivering faithfulness during the complete product life time.

MRO processes are threads of the maintenance of complex capital goods e.g. of aircraft jet engines. In the industrial practice, special MRO-service-providers deal with the maintenance of such aggregates. The service providers go back to competences and capacities of suppliers which execute the real MRO-processes.

The maintenance of complex capital goods, for example the maintenance of aircraft jet engines, represents a special challenge to maintenance supporters due to product complexity and customer requirements. On the one hand, challenges result from the usually unknown product condition, on the other hand from very cost-intensive spare parts. Generally it is difficult to classify expert knowledge, mostly incomplete statistic data of a product and uncertain product conditions in order to forecast the expected maintenance line capacity and part requirements.

1.1 Separation of terms

To develop a better appreciation of the difficulties of the maintenance, at first the terms MRO are separated from each other. The tasks "inspection", "servicing" and "repair / overhauling" are partial tasks of the maintenance as shown in figure 1. During the "inspection", the condition of an aggregate is established, the servicing has to protect a specified condition during maintenance. The processes Repair (R), Overhaul (O) and Replace (P) are integrated into the task "repair / overhauling". The range and duration of these processes are hardly to forecast, due to the fact that the condition of the aggregate is unknown until the inspection process.

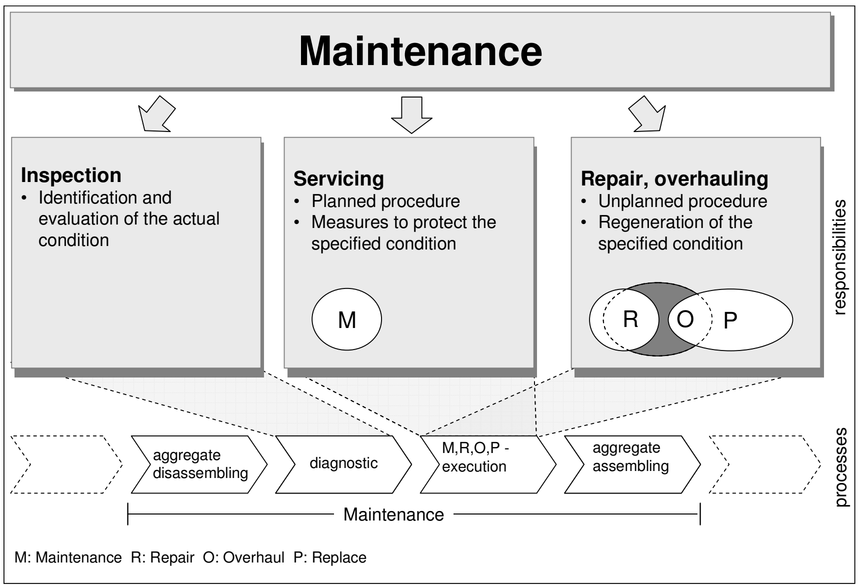

Figure 1: Separation of terms

2. MODELLING ON BASIS OF BAYESIAN NETWORKS

2.1 Product structure

The product structure is based on the parts list. To the German Institute for Standardization [2,3] the product structure forms the order plan after which the drawing and parts list of the product are constructed.

Figure 2 represents a possibility of the diagrammatic representation of a product structure.

On the bases of the product structure, the construction of a multi-level product B_1 can be reproduced. The structure steps appear from the fact that modules or spare parts of a lower level are contained in the higher group.

The representation of the product structure model and calculation of the order probabilities are realized with the help of Bayesian Networks. New is the development of a method to transfer a product structure, as shown in figure 2, into a

Bayesian Network and the calculation of the order probabilities resulting from the Network.

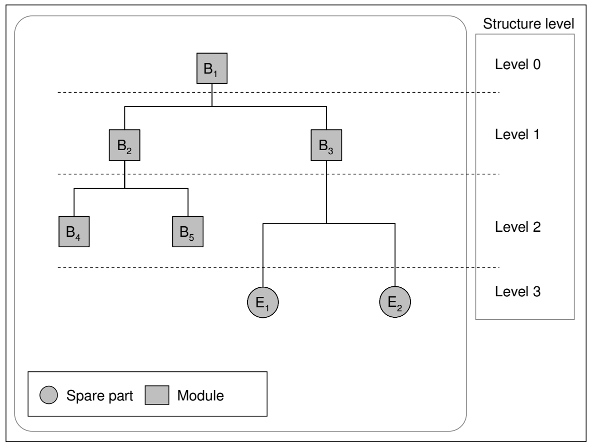

Figure 2: Diagrammatic representation of a product structure

The Bayesian Network is a directed acyclic graph with a set of variables (nodes) and a set of directed edges between the variables. To each variable a table is attached, which contains conditional probabilities of causal relationships [4]. Figure 3 represents an exemplary Bayesian Network.

The respective conditional probabilities between variables can be established for example from appropriate statistic data of past orders or empirical values. The probability of an event or a condition B is called P(B).

P(B) represents a real number in the interval I = [0, 1].

The condition of a situation in which A is true, thus $P(A_{true})$, under the condition that B is true is marked with $A_{true}|B_{true}$. The conditional probability can be calculated by using the Bayes' theorem:

$$P(A \mid B) = \frac{P(A) * P(B \mid A)}{P(B)}$$

Using the beginning probabilities, which are represented as rectangles in figure 3 of the exemplary Bayesian Network, some probability calculations can be executed. Assuming that the index "true", thus B_{true} represents a faultless module, the probability that the module B and the spare parts A and C are also faultless, can be calculated by the Bayes' theorem [5,6]:

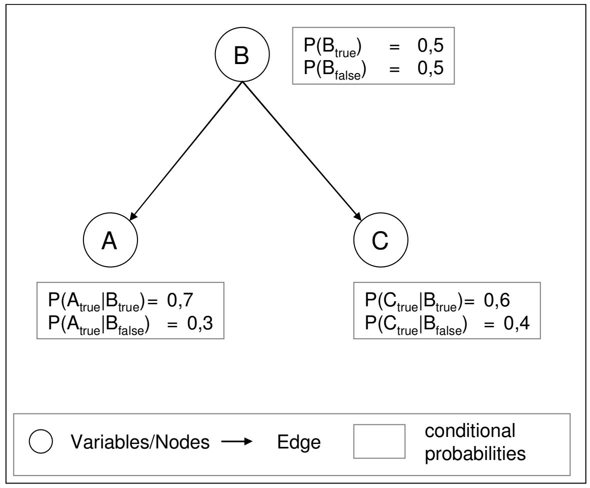

Figure 3: Graphical representation of an example for a Baysian Network

$$P(B_{true} \cap A_{true} \cap C_{true}) = P(B_{true}) * P(A_{true} \mid B_{true}) * P(C_{true} \mid B_{true})$$
$$P(B_{true} \cap A_{true} \cap C_{true}) = 0{,}5 * 0{,}7 * 0{,}6 = 0{,}21$$

The probability for the condition mentioned above in this example amounts to 21%.

A Bayesian Network to calculate the order probabilities can be derived directly from the product structure of the considered product as followed:

- Modules and spare parts are represented as variables or nodes
- Edges arise from the structural product construction
- The probability distribution is determined from appropriate statistic data of past orders

The Bayesian Network modelled in this way also offers the possibility to involve internal and external factors of influence. Internal factors of influence consider the dependences and the mutual influencing between the spare parts of foreign modules or other spare parts [7,8].

External factors of influence for example modules- and spare part age, operating time or points of use have an effect on modules or spare parts from the outside. External factors of influence mostly arise from the application profile of the considered product.

A Bayesian Network serves to represent the common probability distribution of all involved modules and spare parts in a compact way under utilization of known conditional dependences which arise from appropriate statistic data [9].

The condition and therefore the order probability for a module or spare part can be calculated with the help of the Bayes' theorem under consideration of the internal and external factors of influence as mentioned above.

With the placing of order to the maintenance of an aggregate, the Bayesian Network is initialized with all available information including external factors of influence. As a first result, the Bayesian Network will deliver order probabilities. These order probabilities can be used to calculate the needed capacity, for example man power to execute the maintenance or number of needed replacement parts.

3. REPRESENTATION OF UNCERTAINTY

The parts list and the pertinent probability tables of the aggregate are converted in a file format which can be read directly in the software module SMILE (Structural Modelling, Inference, and Learning Engine) [10]. With the help of the software module SMILE, Bayesian Networks can be represented and calculated. The choice of the software module SMILE to the representation of Bayesian Networks and calculation of order probabilities as founded by the free use and availability of the source code.

Figure 4 shows the transfer of the product structure (figure 1) in a Bayesian Network. The rectangular nodes represented in figure 4 represent in each case a module (B_x), a spare part (E_x) or external factors of influence.

External factors of influence, as for example part age, operating time or points of use are ordered in the lower row of figure 4. In the illustrated example the modules and spare parts can accept the following conditions:

- R = Reliable: Spare part is faultless.
- I = In-house: In-house maintenance
- O = Outsource: Outsourced maintenance
- P = Replace: Replacement of a spare part
- M = Missing: Spare part is missing

The order probabilities can be read directly in the respective nodes. Considering the spare part "E1" in figure 4, the probability amounts to 47% that this spare part must be replaced.

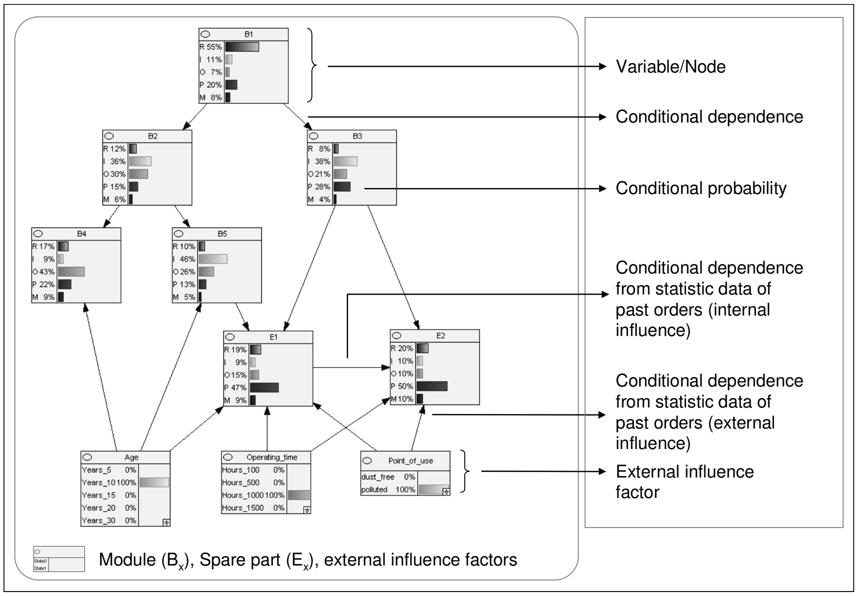

Figure 4: Transfer of the product structure from figure 2 in a Bayesian Network

The order probabilities can be read directly in the respective nodes. Considering the spare part "E1" in figure 4, the probability amounts to 47% that this spare part must be replaced.

4. PROBABILITY-REACTIVE ORDER MANAGEMENT

In the previous section a method for the modelling of uncertainties spare part conditions was introduced.

In the course of the tear-down process, new information about the condition of the already disassembled modules or spare parts are won, which are directed back as a new additional knowledge basis to the Bayesian Network. The Bayesian Network will calculate much sharper probabilities about the condition of the other remaining modules and spare parts.

As already mentioned, probabilities are used to represent the uncertainties about the condition of modules or spare parts.

These probabilities are not static, each aggregate, even identical in construction, has different initial properties caused by the external influence factors.

In addition, not all required informations are available to describe the complete properties of an aggregate. This means that the knowledge about the aggregate condition has to be sharpened during the tear-down process.

These probabilities and information about the spare part condition can be immediately passed to the order release. Considering to the 'Load-oriented order release' (LOOR) [11] that influences throughput times on a shop floor by controlling the amount of jobs released and, thus, the input to the production system, the load limit LL for a work station is calculated as followed:

$$LL(WS) = PSL(WS) + PDL(WS)$$

The variables are defined as:

- WS = work station
- LL(WS) = load limit
- PSL(WS) = average planned stock level
- PDL(WS) = average planned dispatch level

According to LOOR the planned processing times of the n-th work station within the planning period are discounted by using the loading percentage, LOAP which is calculated as followed:

$$LOAP(WS) = \frac{LL(WS)}{PDL(WS)} \times 100\%$$

To pass the calculated probabilities to the order release the processing time for maintenance of a spare part has to be multiplied with the calculated probabilities.

The probability oriented work station capacity is calculated according to the following formula:

$$C(A) = P(A) \times T(A)$$

The variables are defined as:

- P(A) = probability
- T(A) = processing time
- C(A) = probability oriented work station capacity

Relating to the example in figure 4 and looking at the module $B_{5,}$ the probability for in-house maintenance is 46%. Assuming that the processing time for this module is 100 hours, the needed capacity can be planned with 46 hours.

According to the fact the calculated probabilities will change during the tear-down process, the needed work station capacity will change. To handle the variability of the probabilities it is necessary to set the LOAP higher as calculated above. The future work will determine the factor to raise the LOAP by the use of a simulation model.

A further advantage using probabilities calculated by the Bayesian Network is the reduction of disassembling steps. The tear-down order usually arises from the product structure, disassembling steps can be left out in case that the contained modules or spare parts are faultless.

5. CONCLUSIONS AN FUTURE WORK

This paper described a method to raise a condition prognosis of modules and spare parts and the corresponding order probabilities of spare parts during the tear-down process. It is based on a product specific Bayesian Network, which contains information about the condition of spare parts.

Different uncertainties resulting from different influence factors and the possibility to trace back new information during the tear-down process can be represented by Bayesian Networks.

It was shown that the method produces adequate surroundings for predicative and reactive planning.

The next step will be the implementation of a software prototype, which allows a simple creation of Bayesian Networks based on a product structure.

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7. REFERENCES

1. DIN 199, 2003, Technical product documentation - CAD-Models, drawings and items lists - Part 1, Vocabulary, Beuth Verlag GmbH
2. DIN 31051, 2003, Fundamentals of maintenance, Beuth Verlag GmbH
3. Jensen F., 2002, Bayesian Networks an Dicision Graphs, Springer Verlag, New York/ Berlin/ Heidelberg
4. Koch K-R., 2000, Einführung in die Bayes-Statistik Springer Verlag, New York / Berlin / Heidelberg,
5. Sander P., Badoux R., 1991, Bayesian Methods in Reliability Kluwe Academic Publishers
6 Schaffitzel E., Navel H.-Chr., 1995, Optimierungs-ansätze innerhalb der Ersatzteilversorgung – Ebenenübergreifende und sortimentsbezogene Möglichkeiten zur Rationalisierung innerhalb der Vertriebslogistik, VDI Berichte Nr. 1206, : 22
7. Scholz-Reiter B., Höhns, H., 2003, Wissensbasierte Auftragskoordination im Supply Chain Management mit Agentensystemen: Aspekte des Knowledge Engineering zur Entwicklung agentenbasierter dezentraler PPS-Funktionalitäten, Industrie Management Nr. 19, GITO-Verlag, Berlin, 26-29
8. Scholz-Reiter B., Zussmann E., Schnarke H., 1996, Planung in reaktiven Demontageprozessen, Industrie Management Nr. 12, GITO-Verlag, Berlin : 16-21
9. . SMILE (Structural Modeling, Inference, and Learning Engine), 2006, Decision Systems Laboratory, http://genie.sis.pitt.edu
10. Weibel B., 1978, Bayes’sche Entscheidungstheorie Verlag Paul Haupt, Bern
11. Wiendahl, H.-P., 1995 Load-Oriented Manufacturing Control, Berlin et al.: Springer.