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Information Fusion as a means of Forecasting Expenditures for Regenerating Complex Investment Goods

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***Abstract*—**Planning capacities when regenerating complex investment goods involves particular challenges in that the planning is subject to a large degree of uncertainty regarding load information. Using information fusion – by applying Bayesian Networks – a method is being developed for forecasting the anticipated expenditures (human labor, tool and machinery utilization, time etc.) for regenerating a good. The generated forecasts then later serve as a tool for planning capacities and ensure a greater stability in the planning processes.

***Keywords*—**Bayesian Networks, capacity planning, complex investment goods, damages library, forecasting, information fusion, regeneration.

I. Introduction

THE aim of this paper is to increase the logistical performance of regeneration processes. Regeneration is the restoration resp. improvement of the condition of a complex investment good. Complex investment goods in the sense of the target of this paper are such investment goods in which a high number of components stand in diverse functional relations. The processes summarized by the term regeneration pose significant challenges not only for the planning and control of resources but also with regards to their availability. This stems in part from their high complexity and the large number of individual parts but also for example, from the fixed time points for starting and ending the regeneration process combined with the lack of knowledge during the planning stages about how much work will be involved.

In order to meet the extremely high demands on the planning and control of regeneration processes by efficiently planning capacities, information about the use of the object and initial regenerative measures need to be collected as early as possible (Fig. 1).

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However, at this point in time the information concerning the type and scope of the regeneration work is still unclear. Suitable approaches to adequately considering this uncertain information during the planning can be found in reaction methodology. Reaction methodology is characterized by its ability to continually record information from its surroundings and to simultaneously process it [1].

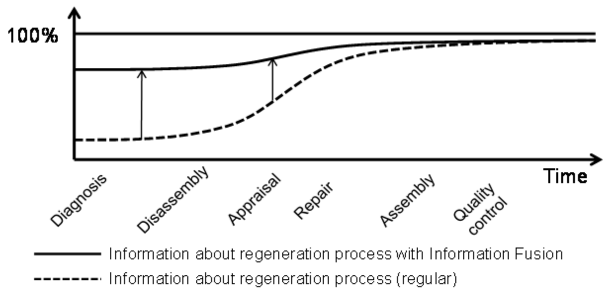

Fig. 1 Information about regeneration process

II. Planning Capacities when Regenerating Complex Investment Goods

Within the frame of Collaborative Research Project (SFB) 871‘s sub-project D1 a method is being developed for efficiently planning and aligning capacities despite the uncertainty of load information (Fig. 2) [2]. In comparison to production planning and control in traditional production areas, capacity planning in regeneration is marked by a growing uncertainty which, due to unforeseeable events, increases along with the complexity of the object. In the practice, this uncertainty is frequently met with a building up of both system and personnel capacities (often leading to unutilized capacities) as well as an extensive stockpile of replacement parts while neglecting the stock and opportunity costs [3]. Particularly with complex investment goods an optimum between sufficient stores of replacement parts and an appropriate level of costs for tied-up capital has to be found in order to ensure efficiency. Consequently, the required expenditures (replacement parts, human labor, tool and machinery utilization, time etc.) for the regeneration have to be forecasted as precisely as possible thus facilitating a detailed capacity planning. Up until now, there has been insufficient research on combining expenditure forecasting with capacity planning, which is why there are no practical approaches for it [4].

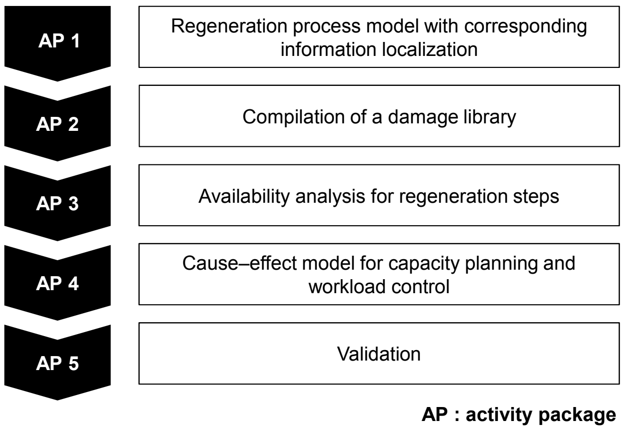

Fig. 2 Activity packages of the project

III. Basis: Generic Process Models and Damages Library

In the course of the sub-project, a generic process model was first developed based on the structure of the SCOR model [6]. In doing so, particular attention was paid to the location of the information since, from a logistical and technical perspective, planning and controlling regeneration processes is dependent on supplying, exchanging and processing information. The standardized, comparable and assessable process model serves as a basis for the product regeneration. Based on the model a library of damages was developed with the goal of making the information more tangible for the capacity planning. This library appears as a relational databank and comprises a collection of interconnected relations as well as a collection of possible errors and damages that can arise while regenerating complex investment goods. The information can primarily be divided into three categories: wear and tear, assessment outcomes and physical regeneration processes. This information can for example contain customer data, usage behavior, signs of damages, part information and detailed data about ‘regeneration paths’ (e.g. systems, setup times and processing times). The information regarding regeneration paths is extended with additional practice based values and thus contains potential workstations that can be used alternatively while the respective damage is being repaired. The regeneration path thus only represents a planning variable for the load of specific workstations and thus influences the quality of the forecasting method developed in the following section.

IV. Forecasting Regeneration Expenditures by means of Information Fusion

The library of damages offers a basis for assessments using statistical methods. Based on the information available at a certain time point (input variables) the information fusion should optimally utilize the ‘knowledge’ found in the damages library and thus anticipate the existing but not yet identifiable damages. Thus with the aid of existing possibilities of artificial intelligence the expenditures arising for the regeneration can be forecasted and suitable strategies for reacting can be developed for every case of damage. The lack of information about the investment good that is to be regenerated requires a method that leads to reliable conclusions despite prevailing uncertainties. It is therefore first necessary to test which learning systems are best suited. The field of application of artificial intelligence provides a variety of methods to choose from including fuzzy logic, Dempster-Shafer Theory, artificial neural networks, Bayesian Networks and case based reasoning. Extensive information on these can be found in [7]-[14].

V. Selecting a Method

Fuzzy Logic is a method for modeling uncertain (fuzzy) linguistic statements or concepts and can be understood as an extension of traditional binary logic or set theory. The method is based on the idea that, to a certain degree, a concrete element can be also be allocated to a set. Fuzzy logic has been successfully applied in controls engineering in the form of fuzzy controllers [6], [7]. *Artificial neural networks* in comparison comprise a number of network models that mimic biological neural networks. They attempt to imitate how information is processed by the nervous system in the human brain [8] and are characterized by their ability to learn. They are not programmed and are instead trained for each type of problem [9]. The *Dempster-Shafer Theory* on the other hand represents a generalization of probability theory and is a theory of plausible reasoning when there is uncertainty. In consideration of their credibility various statements (so-called ‘evidence’), often from unreliable or contradicting sources of information, are combined into an overall statement [10], [11]. *Cased Based Reasoning (CBR)* falls into the category of mechanical learning systems. There is a basis of knowledge that does not contain any generic rules but rather a collection of problems that have already been experienced and their respective solutions. When a new problem arises, for which there is no available solution, relevant solutions for similar problems are drawn upon and adapted to the current situation [12]. A *Bayesian Network* is a graph based method which, by means of conditional probabilities, draws conclusions despite uncertainty [13]. Bayesian Networks are directed acyclic graphs which consist of nodes and edges. The nodes represent events or random variables, each of which is allocated a finite set of mutually excluding conditions. Every condition of a node is linked to the probability of it appearing. The edges represent the direct dependency of a node (child) to other nodes (parents) [14].

Each of these methods has specific advantages and disadvantages for various application areas or types of problems. With the aim of being able to make forecasts regarding regeneration based on the library of damages, there are different criteria for evaluating these methods (flexibility, forecast quality, effort required to make forecast, transparency and compatibility with damages library). Out of all of these methods the Bayesian Networks was the only one which fulfilled all of the required criteria and was therefore selected for the information infusion (Fig. 3). It should be noted however that this does not exclude using the other methods in

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the product regeneration. Combining a number of information sources has the potential to increase knowledge about relevant factors for the decision making and to optimize the capacity planning.

Evaluation Criteria	Methods				
	FL	ANN	DST	CBR	BN
Flexibility	-	O	O	+	+
Quality of Forecast	O	+	O	O	+
Effort Required to Produce	-	O	-	+	+
Understandability	+	-	O	+	+
Compatibility of Damages Library	+	O	-	-	+

Evaluation of Criteria: + completely fulfilled o neutral / inapplicable -not fulfilled

Abbreviations: FL – Fuzzy Logic; ANN – Artificial Neural Networks; DST – Dempster-Shafer Theory; CBR – Cased Based Reasoning; BN – Bayesian Networks

Fig. 3 Evaluating Forecasting Methods

VI. Developing and Applying Bayesian Networks

With the aid of Bayesian Networks it is possible to create forecasts about the expenditures involved in regenerating complex investment goods. At the same time these forecasts form a tool for optimizing the capacity planning when there is uncertain information about the load. The damages library serves as the basis for developing the forecasts. In developing a Bayesian Network it is first essential to formulate the goal of the network i.e., to clarify the purpose of the network or which conclusions the network should calculate. In our case, as described by our aim, the probable expenditures for the regeneration should be calculated from the information entered into the network. Once the goal has been set, it is necessary to define the nodes, that is, to set the variables or events that are to be reproduced in the network. The information that is to be fed into the network is referred to as input variables while the resulting regeneration expenditures are referred to as output variables (or outcomes). Each variable is allocated to one node thus creating input and output nodes. Supplementary to this, each of the individual, mutually excluding conditions of the nodes are defined as discrete or continuous. In situations where a node represents a continuous variable, discrete subsets (conditional clusters) form the continual variables. Once this step has been completed, the structure of the network is set by determining the parent and child nodes as well as by positioning the edges. In our case, each input node has to exhibit exactly one link to each output node. Since Bayesian Networks are able to draw conclusions both inductively and deductively, it is possible to define both input and output nodes as either child or parent nodes. The next and final step involves the network itself learning the conditional probability tables (CPT). The connections between the nodes are weighted against each other. This weighting is represented in the child nodes through the CPTs. The child nodes are learnt based on historical data (case studies) saved in the damages library and can be manually adapted as required at a later point (Fig. 4).

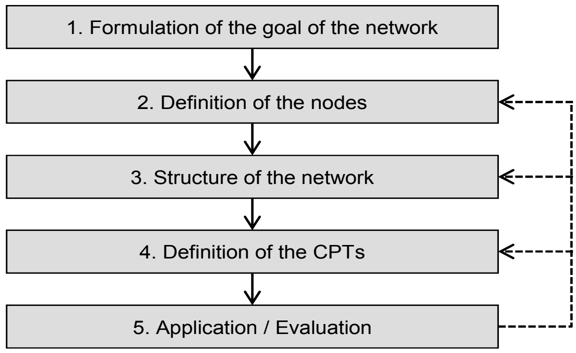

Fig. 4 Developing and applying a Bayesian Network

Following that, the Bayesian Network is fully functional and can be supplied with existing knowledge about the expression or probability of the conditions for each of the input nodes. This knowledge is referred to as "findings" and can be broken down into three different types. Precise knowledge about the definite existence of a condition and whose probability is thus 100% is referred to as a "positive finding". In comparison, a "negative finding" means that a condition is definitely not present; the probability of it is thus 0%. Between these two is uncertain knowledge, referred to as a "likelihood finding" and whose value is an estimate of the probability of this condition arising. Adjusting the probabilities of the conditions for the output nodes ultimately forms the conclusion and forecast of the network. This also applies in the case where there is no knowledge about the condition of one or more of the input nodes. The calculation is based on the relative frequency of the conditions set by means of the case studies and historical data when defining the nodes. Nonetheless, the more knowledge that flows into the network, the more differentiated the forecast is.

VII. Validation

Generally speaking, there are two forecasting possibilities for planning capacities: the top-down method and the bottom-up method. In this context, top-down means that based on the forecast of the total load for regenerating the complex investment good, forecasts or plans for the sub-areas can be made. In comparison, bottom-up refers to planning starting with the forecasts for the sub-areas (e.g. accounting units) and working up to the expenditures for regenerating entire investment goods. In order to precisely and efficiently plan capacities it is critical that more than a rough framework is considered; forecasts that can subsequently be combined need to be developed up to and including the component and workstation levels. Bayesian Networks have the potential to generate detailed forecasts for the various levels. The abilities of the developed networks were validated within the framework of a prototypical practical application. The practical application shows that only the top-down method is suitable for reliable results. Every level has to be planned with a different planning horizon, input variables and parameters. It appears that based on the input variables the networks create suitable conclusions for planning capacities. Later practical application is supported by the fact that Bayesian Networks are not a closed unit, but rather can be extended by inserting new nodes or supplementing the CPTs with expert knowledge or current case studies. Based on an actual case study the forecasted expenditures for an entire complex investment good along with the individual components, parts and loads on a workstation level were observed and evaluated. The evaluation showed that the forecast quality was high. The implementation of Bayesian Networks in regenerating complex investment goods can thus clearly be positively evaluated and can serve to optimize the capacity planning. In the future it is possible to develop completely new networks for different problems such as for investigating the correlations between various types of damages for the complex investment good. It is imaginable that causal correlations might be found here which in turn could be beneficial during planning process. Bayesian Networks also have the potential to make other helpful forecasts beyond capacity planning and to increase the planning certainty.

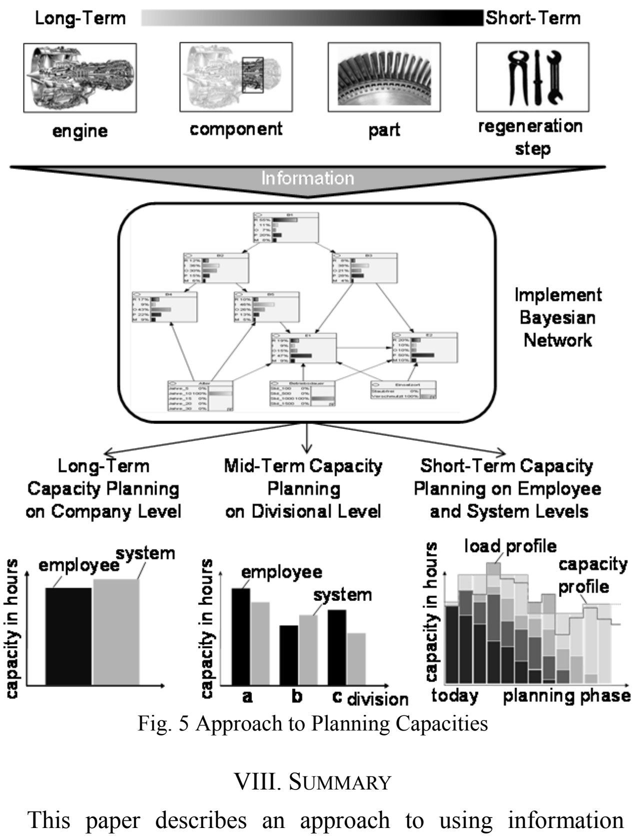

Fig. 5 Approach to Planning Capacities

VIII. Summary

This paper describes an approach to using information fusion to forecast expenditures for regenerating complex investment goods – despite uncertain load information. Implementing Bayesian Networks in actual test cases has demonstrated that the generated forecasts for different levels could be very positively evaluated (Fig. 5).

The networks allow valid statements regarding the anticipated regeneration expenditures to be drawn and can thus provide considerable support in planning capacities. The quality of the forecasts can also be increased in that the underlying library of damages, as a database, can be further rounded out with additional case studies. It should be noted however that Bayesian Networks do not replace previous methods, but rather serve to supplement them. The forecasts can make previous estimates about regeneration expenditures more precise. At the same time, the available knowledge can change how the forecasts are dealt with and strengthen or relativize the information garnered from them. Based on the forecasts as a tool for planning capacities, an algorithm will be developed in the next step in order to draw conclusions about the required capacities from the forecasted expenditures. Moreover, it may be practical to combine other artificial intelligence methods with the Bayesian Networks in order to further optimize the potential for capacity planning.

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