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Process planning in special machinery: Increasing reliability in volatile surroundings

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Abstract

In Germany the growing demand for customized systems and integrated solutions in machinery enhance the importance of special machinery. Within this industry, the commissioning process represents a significant part in the product engineering process and forms the base for reliability and performance during future operation. However, there is little research focusing on this process for special machinery. In particular, there has been little discussion on methods to evaluate alternative test processes or arranging test processes along the commissioning process. Therefore, this paper develops an application-oriented simulation tool that allows an evaluation of test alternatives and an arrangement of test processes during the commissioning process in special machinery. The authors decided to use Bayesian Networks to model the commissioning process as they enable the connectivity of multiple modules and integrate the stochastic dependencies along the processes. In addition the paper reveals two concepts to deal with unknown processes and the lack of data. Applying the simulation tool in a laser system manufacturer reveals that the simulation tool allows an evaluation as well as the identification of risks and need for countermeasures.

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Keywords: Special machinery; Commissining process; Bayesian Networks; Fuzzy sets; process simulation, expert knowledge

1. Introduction

Cooperate studies from VDMA and McKinsey reveal that the German machinery industry identified an increasing demand for customized and integrated solutions [1]. This trend drives machinery manufacturers to offer specific engineer-to-order solutions with low quantities which characterizes them as a special machinery constructor [2]. Within special machinery the commissioning process is an important process as it accounts for 15% to 25% of the overall lead time [3]. This phase encounters increasing complexity [4] while having decreasing time available for completion [5]. Therefore, a high importance lies in speeding up the commissioning process. According to Buchholz [6] long lead times, adherence to delivery dates and complexity of interfaces are the main challenges for special machinery constructors. These imply problems for speeding up the commissioning process as they lead to difficulties when evaluating different or changed processes and methods in order to reduce the lead time. While prototypes and pilot series enable testing and thereby establish an evaluation basis [7] as well as learning in a serial production [8], they are far more cost and time-consuming in special machinery. Therefore, this paper presents a methodology for special machinery to allow an evaluation of processes during the commissioning process based on simulation. The simulation uses Bayesian networks to model the commissioning process as they can handle uncertainties well [9]. This simulation

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enables easy usage for production planning, when process changes are to be assessed. These changes include replacing existing commissioning processes by alternatives or reordering the process sequence.

2. Characteristics in special machinery

Special machinery solutions gain more importance for German machinery constructors as they pair innovations with customized solutions and thereby establish themselves as stand-alone suppliers in a certain area [10]. Special machinery is characterized by engineer-to-order solutions that often include an individually aligned production process [2]. These customized solutions require a high engineering effort [11,12] but are associated with small quantities and a large share of manual work. Manual processing time and lack of data respective the small amount of available data, make data acquisition for simulation input difficult [13]. In this case expert knowledge can help collecting relevant data. Even though acquiring technical knowledge is not a strength of expert interviews, there are little alternatives when the relevant data is not available [14]. Furthermore, experts often use vague expressions in interviews. Therefore, Section 2.3 gives a brief introduction in dealing vague knowledge by using fuzzy sets.

2.1. Commissioning process within special machinery

The main task in the commissioning process is "to establish the functionality and the functional interaction of previously assembled components as well as their testing" [15]. The commissioning process is challenged by complexity, time pressure and concurrency of errors [5]. With the first alignment of different components the technical problems usually increase [16]. These problems are cost-intensive and time-consuming and can cause delays. Furthermore, the commissioning process accounts for capital commitment costs as well as a shortage of available space on the shop floor [17]. Paired with the long lead times, high capital costs and the complexity in special machinery, the commissioning process represents a high saving potential for special machinery manufacturers. While a large amount of studies focused on the commissioning process along the ramp-up of serial production, very little research is conducted on this process in small-scale production environments such as in special machinery.

2.2. Bayesian Networks

Bayesian Networks also known as belief networks are directed, acyclic graphs (DAG). The nodes represent random variables which are connected by directed edges modeling the cause-effect relation [18]. The strength of these dependencies is based on the conditional probability and can be calculated using Bayes' theorem [9]. They have the advantage of being able to model uncertainty and combining data from diverse origin [19,20]. Furthermore, they proved to handle complexity by decomposability [9,20]. Moreover, Bayesian Networks are easy to update and, therefore, suited in a dynamic environment [21]. Thus, they are often used for decision, failure and risk analysis [19,22–26].

2.3. Data acquisition

In special machinery there is only a small amount of available data. Therefore, expert knowledge plays an important role in the data acquisition process before starting a simulation. Expert knowledge is vague and subjective [20,2]. Fuzzy sets are an opportunity to deal with vague knowledge [27]. They include a membership function that makes a statement on the degree of membership of an element to a specific set [9]. This "provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria of class membership" [27]. Therefore, various authors use fuzzy sets for safety and reliability analysis to deal with human influences such as expert knowledge [28–32]. As research has shown, fuzzy sets are a proven concept to deal with vague knowledge and can help to acquire data in a special machinery environment. However, simulation results largely depend on the quality of input data [13]. Therefore, additional concepts to secure high input quality of expert interviews are presented in this paper.

2.4. Simulation for an evaluation of process sequences and alternatives

A simulation models a system under dynamic influences and enables the transfer of findings to a real system [33]. In order to run simulations a precise simulation model is needed. This model is build by reducing and abstracting the real system. Afterwards, the model can be used for experiments. As soon as the results of the conducted experiments are available, they can be analyzed and interpreted to gain a conclusion. Based on the conclusion changes for the real system are initiated. This simulation process is usually understood as a repetitive loop [13]. The following Fig. 1 illustrates this loop.

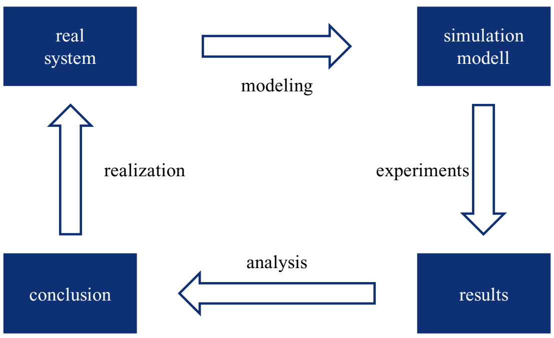

Fig. 1: Simulation process as a loop according to [13]

In the last years, the usage of simulation in production planning environment has increased. Multiple software companies offer simulation solutions for e.g. factory planning, logistics systems, robots or ergonomics and allow an optimization of specific production planning tasks [34–38]. These simulations focus on the exact function and interaction of the modeled system and its components. Therefore, they need deep knowledge of the system and its individual components. However, for a process evaluation, as discussed in this paper, it is sufficient to model the cause-effect relation of quality, time and costs. Thus, a simulation model that allows modeling a commissioning process without displaying the functionalities of each individual system component seems desirable. Furthermore, commercial simulation tools assume a constant quality for their process simulations [5]. This conflicts with our goal to assess how the quality is influenced by process changes and to vary the quality states at the beginning of the examined process.

3. Applied simulation model for special machinery

When special machinery manufacturers analyze their processes in order to gain improvements regarding time, cost or quality aspects, they often need to establish changes. Depending on the scope of the process changes, the impact is often hard to evaluate previously. Given the small quantities, the long lead times and the cost intensity of customized machines, prototyping does not seem to be a suitable option in every case. Thus, simulating the process changes enable a pre-assessment. As Fig. 1 shows, the simulation process contains the transfer of the regarded system into a simulation model. This step is crucial for the success of the simulation as an inadequate simulation model holds the risk of misleading conclusions. Therefore, this paper addresses primarily the modeling process including:

1. Development of a generic module for the commissioning process in special machinery
2. Data acquisition concepts for expert knowledge

The concepts help to increase the quality of the simulation as well as allow a versatile usability in special machinery. Both are outlined in the following segments

3.1. Development of a generic module for the commissioning process in special machinery

Every process in commissioning consists mainly of four elements forming one module [39]. At first, the entrance state, second, the test process, third, in case needed, the repair process and fourth, the effect state at the end, which then is the entrance state for the next process. Before starting a specific test that examines the functionality of individual components or modules, the system is in a specific state. Considering the observed functionality, there are two states possible. Either the system is fault-free or it is not. In the second case, there will be different types of faults depending on the functionality. Each state and fault type has a likelihood of occurrence.
A second element is the test itself. The test can be eliminated completely or replaced by different test alternatives. Each of the test alternatives has an individual uncertainty of displaying the real test results [40]. This affects the state of the system at the end of the process. Moreover, each test has a specific duration.
The third element models the repair process. This process can be divided into the sub-processes searching, dismantling, repairing and rebuilding [39]. Not each repair process includes all of these sub-processes, but on the other hand the duration of the not existing sub-processes can simply be zero. Furthermore, the durations for these sub processes depend on the types of failures. It has to be emphasized, that this model establishes one defining assumption. In case the test displays a fault, the system must be repaired and the functionality must be completely available after the repair process.
The last element represents the effect state at the end of the process, the failure consequences [39]. It describes the effects that can be caused by entrance states. The system can be fault-free as well, have the same fault as before or have subsequent faults. The latter two can only be the case if a) the test has not been conducted or b) the test displays a wrong result, caused by the test/measurement uncertainty. The four elements are illustrated in Fig. 2 and form the sequence of the simulation tool.
The above explained elements are modeled as a Bayesian Network. The entrance states as well as the state at the end are each represented by a nature node that contains the likelihood of occurrence for every state respective fault. The test uncertainties are also modeled by a nature node. All the sub-processes of the repair process are represented by utility nodes that contain duration of every task in dependency of the failure type. Furthermore, a decision node is introduced to model the decision for a test alternative or the elimination of an existing test process.

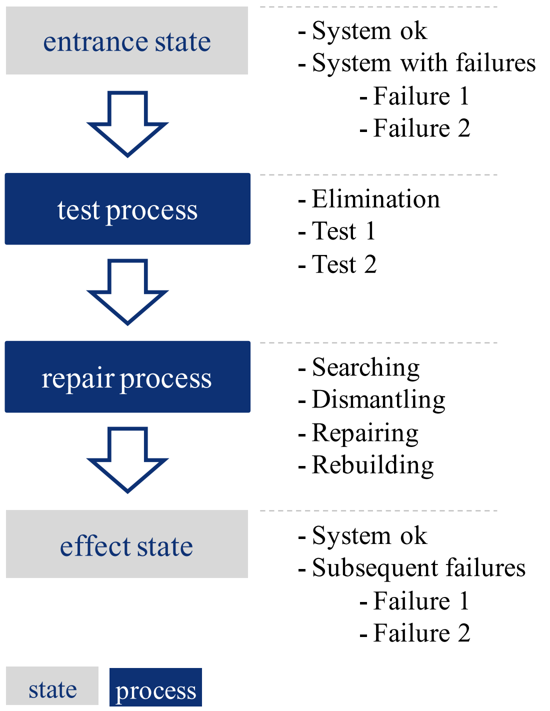

Fig. 2: Generic module for the commissioning process (own figure)

3.2. Data acquisition concepts for expert knowledge

For a simulation the developed model with its four elements needs input data. This includes states, the likelihood of occurrence of these states, durations of processes, test uncertainties as well as subsequent faults with their likelihood of occurrence. In special machinery environments the availability of this data can be challenging. If available, data should be acquired by resources such as data sheets, technical specifications or historical data. However, especially for new or changed processes, data can often be acquired by interviewing experts only. Even though the states themselves, such as fault types or subsequent faults, are in most cases easy to name for experts, assigning likelihoods are not. Therefore, it seems important to help experts by estimating probabilities and thus increasing the accuracy of the data. The two following concepts can help experts.

3.2.1. Comparing to reference points

This concept helps experts in case they have only little experience with the process or can only estimate data such as durations or likelihoods for new processes or processes without available data. For each unknown process the experts are asked to look for two existing and well documented processes for which the relevant data is known. Each of the two processes represents a reference point, comparable to reference prices [41–43]. The first reference point establishes the upper bound, the second the lower bound. Thereby, the experts have introduced a corridor for the unknown data as shown in Fig. 3.

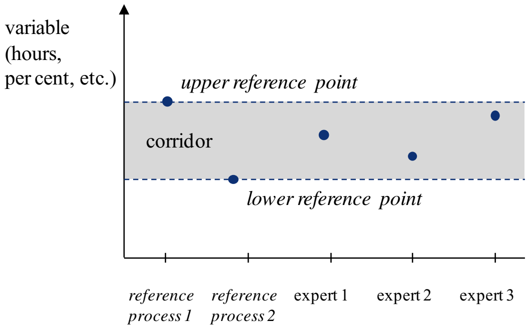

Fig. 3: Reference points establish estimation corridor

The smaller the corridor, the more accurate the estimation will be. After the definition of the corridor each expert estimates the relevant number.

3.2.2. Divide into unknown and known fraction

This concept primarily helps experts to estimate durations. When comparing existing processes with new or changed processes, there are usually new tasks as well as existing tasks. In this case, the process should be divided into existing tasks and unknown tasks. Thereby, the data for the existing tasks can be acquired from historical data. This leaves only the unknown tasks for an expert estimation. As described in a), the experts can establish a corridor for the unknown tasks and, therewith, minimize the uncertainty as far as possible. By this, the uncertainty is caused only by the unknown task and not by the entire process. For likelihoods or test uncertainties the applicability of this concept is only limited, as the influence of unknown tasks on the entire process and the probabilities of its states are not known previously.

3.2.3. Introducing fuzzy logic for vague expressions

Furthermore, when acquiring data from experts in interviews, the answers are often vague. Especially, if they are asked to estimate the likelihood of occurrence for certain states, they use verbal expressions such as 'high' or 'low' etc. Although the interviewer can simply not allow these expressions, there is another way of dealing with them. These verbal expressions can be transferred with fuzzy logic into usable data in order to run a simulation. Common expressions for probabilities are in our context: 'very high (vh), high (h), middle (m), low (l) and very low (vl)'. In order to transfer these expressions, this paper uses the following membership functions as described in equation 1 and illustrated in Fig. 4.

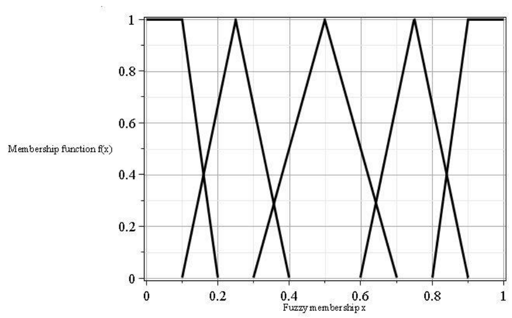

Fig. 4: Fuzzy function

$$
\begin{aligned}
f_{vh}(x) &= \begin{cases} 0 & x < 0.8 \\ \dfrac{x-0.8}{0.1} & 0.8 \le x \le 0.9 \\ 1 & x \ge 0.9 \end{cases} \\
f_{h}(x) &= \begin{cases} \dfrac{x-0.6}{0.15} & 0.6 \le x < 0.75 \\ \dfrac{0.9-x}{0.15} & 0.75 \le x \le 0.9 \\ 0 & \text{otherwise} \end{cases} \\
f_{m}(x) &= \begin{cases} \dfrac{x-0.3}{0.2} & 0.3 \le x < 0.5 \\ \dfrac{0.7-x}{0.2} & 0.5 \le x \le 0.7 \\ 0 & \text{otherwise} \end{cases} \qquad (1) \\
f_{l}(x) &= \begin{cases} \dfrac{x-0.1}{0.15} & 0.1 \le x < 0.25 \\ \dfrac{0.4-x}{0.15} & 0.25 \le x \le 0.4 \\ 0 & otherwise \end{cases} \\
f_{vl}(x) &= \begin{cases} 0 & x > 0.2 \\ \dfrac{0.2-x}{0.1} & 0.1 \le x \le 0.2 \\ 1 & otherwise \end{cases}
\end{aligned}
$$

3.3. Simulating using Bayesian Networks

The introduced Bayesian Network is used as a simulation model. After inserting case-specific data, random cases are generated by a variation of likelihoods of occurrence at the entrance state as well as a variation of the durations of the sub-processes. The variation at the entrance state simulates different quality conditions at the beginning of the process.

The variation of durations represents the deviations in process durations.

If the simulation serves as an evaluation tool for two or more process alternatives, the alternatives are compared by using one module and vary duration and entrance likelihoods. In case that an assessment on the order of processes is needed, the same module is used. Multiple of these modules are connected with each other and thereby modeling the examined commissioning process. Here each process position is tested additionally and, thereby, assessed which position in the process enables the best solution.

4. Discussion

Using Bayesian Networks for planning of the commissioning process in special machinery and thus reducing duration has been proven [39]. Based on this model, the authors cluster four elements in order to establish a module that allows comparing different test alternatives with each other as well as arranging test processes along the commissioning process. This module is implemented as a simulation tool that enables the user to run simulations by generating random cases. The paper reveals that the simulation not only allows a statement on the suitability of test alternatives or the best position, it also indicates risks of decisions as well as the need for countermeasures. Moreover, the tool gives an outlook which alternative fits best for a certain scenario. The tool has proven to be adaptable within the evaluation of processes by connecting multiple modules. By using the tool, the user does not have to know the Bayesian Network that models the commissioning process or Bayesian graphs at all. This allows all engineers and technicians to use the tool for process planning.

While the tool secures an adequate modeling of commission processes, there are still obstacles to handle. As stated above, the results of the simulation largely depend on the quality of the input data. Especially in special machinery the knowledge of experts plays a big role. Therefore, two data acquisition concepts are introduced that help securing the accuracy of the input data. First, by comparing unknown likelihoods or durations to existing data, two different reference points are established. Second, new or substantially changed processes are divided into known and unknown process fractions. Thereby, the uncertainty is reduced to the unknown fraction.

Moreover, the authors use a fuzzy set in order to transform vague expression of experts into usable data for the simulation tool. Thus, experts do not need to translate their expressions in discrete numbers or use a dictated scale.

5. Summary and Outlook

The authors describe the implementation of a simulation tool using Bayesian Network to model commissioning process in special machinery. By establishing a module consisting of entrance state, test decision, repair process and end state, the simulation tool allows an evaluation of different test alternatives and arranging tests along the commissioning process. The simulation identifies risks of decisions as well as implies the need of countermeasures previously. Furthermore, the paper introduces two concepts to deal with the lack of data in special machinery environments by helping experts to make accurate estimations for unknown processes. Additionally, the authors use fuzzy functions to allow vague expressions in expert interviews. However, these concepts do not eliminate the uncertainty that arises from the lack of available data. Therefore, further studies should develop methods to collect data in engineer-to-order industries. Furthermore, additional concepts to increase the accuracy of estimation about unknown processes should be developed.

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