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Situation-based Methodology for Planning the Commissioning of Special Machinery using Bayesian Networks

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Abstract

In German mechanical engineering customized systems and integration solutions are the biggest trends which are mainly applied in special machinery. This paper shows a method to decrease test and commissioning time by using expert knowledge and by considering the risk of failing processes. In literature and practice there is a wide research on virtual commissioning. However, research on methods to optimize production is very rare for complex machinery. In the proposed method, for planning and adapting processes, the authors use heuristics because of their ability to optimize processes using expert knowledge. For the decision of the right application of a heuristic, Bayesian Networks are applied to rate and compare different alternatives. Thus, the result is a method which allows to rate the processes with the needed time and the possible risk for an elimination and a substitution of these processes. Using this method the throughput time of a laser system in production in one single commissioning process is decreased in the validation example by approximately three days.

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Keywords: Special Machinery; Bayesian Networks; Process Heuristics; Process Optimization

1. Introduction

The trends of customized systems and integration solutions are mainly driven by the customers demand for more complex products [1,2]. Thus, the impact of developing more and more complex products with the known methods is an efficiency loss along the product engineering process [1]. The commissioning time is about 10-25% of the throughput time of the product engineering process [3,4]. It varies because of the differing products and their complexity. Compared to serial production, special machinery requires a high engineering effort. Nevertheless, the adaption and precision of the product at the commissioning processes are not comparable to those of serial products. Consequently, efficiency losses caused by the process complexity, the human influence and the low degree of automation have to be accepted [5,6]. Those effects get more important the higher the complexity of the product is [7,1].

Working with known methods like virtual commissioning, especially with complicated products, the effort to build a model is high [8]. Thus, the efficiency of the product engineering process is affected and there is a potential to increase process efficiency.

The major source of delays in test and commissioning is the error containing definitions of upstream sectors which mainly consists of error handling times and waiting times [3].

Furthermore Fig. 1 shows the shares of processing time compared to the idle and waiting time. The processing time is divided into the planned processing time and the processing time caused by technical incidents. To shorten the processing time, caused by technical incidents, the processes with the highest risks have to be identified and dealt with.

In the next chapter an overview on special machinery, Bayesian Networks, process heuristics and risk assessment is given to describe the basics of the proposed method. Following the state of the art in commissioning in special

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machinery and process planning is described. On top of that an approach in process optimization, the virtual commissioning, is explained.

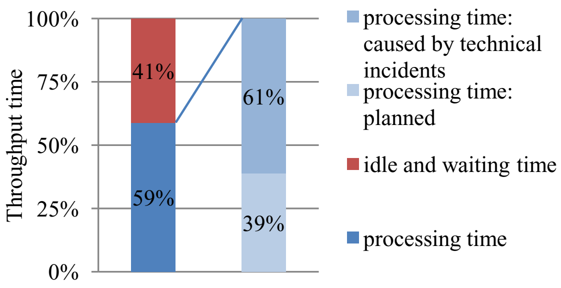

Fig. 1 Throughput time shares of a commissioning process [3]

Concerning the concept of the paper, the authors propose an approach to decrease test and commissioning time by assessing the risk and the duration of processes. To achieve this goal process heuristics to model the process adjustment are described. To combine the process model with the risk analysis and to integrate the existing expert knowledge Bayesian Networks are used.

For validation purposes, the method was applied in an industrial environment. In the evaluation the results of the validation of this case are outlined. Finally a summary, a discussion and an outlook are shown.

2. Basics

The content of this chapter is to summarize the basics which are needed to understand the concept of the production planning in special machinery with Bayesian Networks and process heuristics. Furthermore risk assessment methods are depicted.

2.1. Special Machinery

The field of special machinery can be described as a product engineering process for specialized machines with a high standard. The quantity of the produced parts is very low or even just a single machine is produced. Thus, methods of serial production have a limited application in special machinery [9].

Special Machinery can be found in all industry sectors of mechanical engineering [10]. Consequently, the produced products differ in various ways. Especially the batch size of often just one machine and the individual requirements of the customer show effects on the production and commissioning processes. Therefore, the main focus is on one customer and not on the requirements of a whole market [11]. This property influences the commissioning processes because of the low batch sizes and the missing ability to learn during ramp-up processes.

2.2. Bayesian Networks

Bayesian Networks are directed acyclic graphs which use the Bayes Rule. The prior probability $P(w)$ describes the probability of the event w. $P(w|z)$ is called the posterior probability and $P(z|w)$ is the likelihood of z in case of w [12].

$$P(z|w) = \frac{P(z)P(w|z)}{P(w)} \quad (1)$$

Bayesian Modeling involves mainly two concepts. The first one is to model the probability of certain states. The second one is the utility to calculate the possible outcome. Thus, benefits and costs can be involved into the model [12].

Bayesian Networks are graphical ways to show dependencies between variables in a model and to combine the several calculations of the Bayes Rule [13]. Therefore, they represent a way to create a model in a very wide range of applications. Bayesian Networks focus mainly on decision analysis, risk analysis and failure data analysis [14–18]. The ability to represent conditional dependencies between a set of random variables makes them a tool which can be applied in expert systems [13,19]. Bayesian Networks are able to adapt and model expert knowledge or learn from cases [20,21]. Transition phases show similar properties like the ramp-up phases. The use in transition phases was shown by Nembhard [22]. Thus, the process optimization in special machinery shows a high potential to be supported by Bayesian networks.

2.3. Process Heuristics

Heuristics are defined as a “support and guidance during the search for solution on the basis of heuristic principles” [23]. Heuristic principles are described as the optimization with limited theoretical knowledge and with, compared to other methods, less effort to achieve the goal [24]. Process heuristics are for example the elimination of activities, the combination of activities, the changing of the order of activities, outsourcing of activities, simplification of activities and the parallelization of activities [24]. Consequently, expert knowledge is important for the decision which process heuristics can be applied. The wide application possibilities of heuristics allow the combination with process landscapes to support decision finding.

2.4. Risk assessment

As methods for risk assessment mainly the Fault Tree Analysis (FTA), the Event Tree Analysis (ETA) and the Failure Mode and Effect Analysis (FMEA) are found in practice [25]. All of them are displayed in a tree structure which generates the possibility to rate the failures or risks for example with the indication of the likelihood of occurrence [24].

Those methods do make a causal dependency between events which are not quantified. Thus, the guaranty of a realistic risk assessment is not given. Methods to model certain failure situations do not exist.

Risk management deals with the application of the detected risks in practice. In Fig. 2 the implementation of a risk management system as described in DIN ISO 31000 is shown. The steps can be realized as a continuous improvement in risk handling [26].

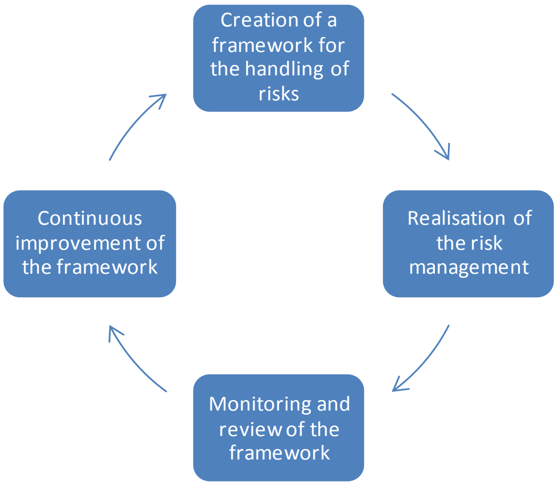

Fig. 2 Relationship between the elements of risk management [26]

3. State of the Art

In the following chapter the commissioning in special machinery is examined. To look deeper into the process itself, current research approaches in process planning and optimization are shown. In conclusion the method of virtual commissioning is outlined.

3.1. Commissioning in special machinery

Commissioning in special machinery is a major part in the product engineering process. Fig. 3 shows the commissioning and ramp-up phases in the context of the product engineering process. Commissioning and ramp up resemble each other despite the fact that the commissioning process takes place at the manufacturing companies' site and the ramp up takes place at the customers' site [27].

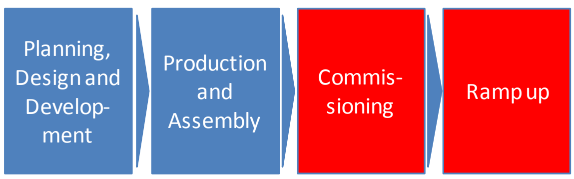

Fig. 3 Phases in the product engineering process cf. [27,8]

The low number of produced machines contributes to the high costs of development in the product engineering process [28]. Furthermore, processes which are executed for the first time have to be considered to take longer than products in serial production like the law of learning in industrial production states [29]. Another property of special machinery is the time consuming changes during final assembly or commissioning processes. Consequently, the aspired product and process quality can only be achieved in the final assembly and commissioning [30]. There are different ways to handle these problems. Process planning, approaches in optimization and preventive methods as virtual commissioning can be adapted from serial production.

3.2. Process planning

Process planning in the commissioning is a topic which has very sparsely been regarded in recent literature. Only in methods used in general production environments like process landscaping disjunctive graphs and process scheduling can be applied and visualized.

For machining on several production machines, planning and scheduling processes can be executed with knowledge-based approaches [31]. Process landscapes like the example in Fig. 4 assist the documentation of business processes, the analysis of process improvements and the workflow management [32].

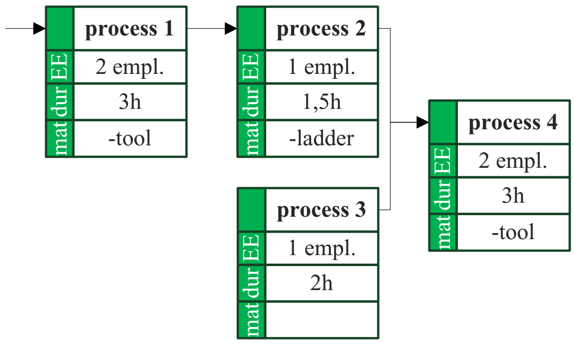

Fig. 4 Process map with a logical connection of each process

3.3. Virtual commissioning

According to Schlette, a prototypical process is developed by process experts who do a sequential development with a lot of changes within the process [33]. However, in literature and practical application virtual commissioning is mainly applied to simple and sometimes complicated tasks. The application to complex production processes or products is not common because of the high modeling efforts.

4. Situation-based Methodology for Commissioning

This approach on planning the commissioning of special machinery is using Bayesian Networks to support risk assessment on individual production processes. The main focus is on the combination of expert knowledge and a production plan to reduce the average throughput time for the commissioning process. Furthermore, the quality of the product is another relevant factor and has to remain stable.

As the foundation of the production planning the authors use the method of process landscaping, in which individual processes can be set into relation. This is done by splitting up processes into sub processes and bringing them into a logical order.

In the process development the process landscapes are mainly designed knowledge-based with logical structures. The goal of the production planning in commissioning is to define the content and the right sequence of the processes. Applying the expert knowledge on known processes and on the creation of new processes, the production planning has to set each process into a logically justified relation.

By splitting up the processes, the categorization between known processes and new processes has to be done. To rate the known processes, data from produced systems can be used for calculation. Looking at the newly, planned processes, expert knowledge on the content of the processes has to be available.

As seen in Fig. 4, the decision of the applied process is combined with a matrix of the time needed. Using this methodology processes can be set into relation and their duration can be compared directly.

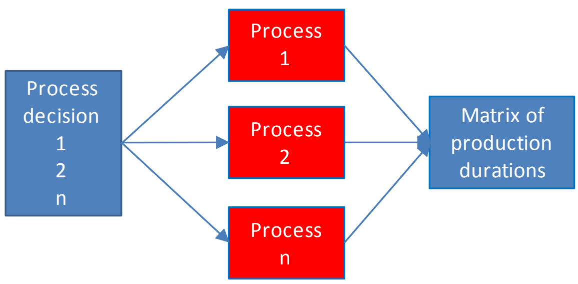

Fig. 5 Process validation using Bayesian Networks

Besides of the regular commissioning process, processes for the reparation of certain adjustments are mapped as shown in Fig. 6. Necessary durations for the search, the reparation and the recovery of the system can be estimated.

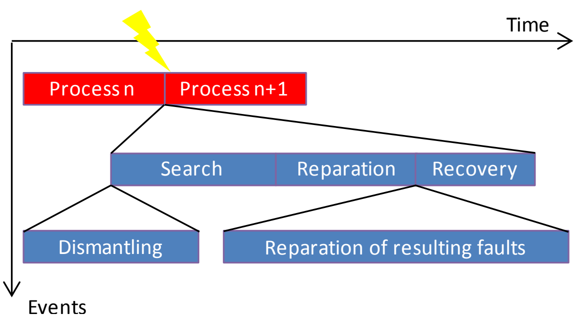

Fig. 6 Process of repairing during commissioning

Furthermore, two more processes, the dismantling and the reparation of resulting failures, are possible options. If needed, more options can be added. The sources for known failures and the failure estimation for new processes are the risk assessment methods like FTA, ETA and FMEA.

To achieve a realistic application area of the applied processes, they have to be combined with the state of the adjustment of the machine. By knowing the state of the machine, the risk of resulting failures of the machine can be assessed. As there is no possibility to make a prediction of the state of a future machine, the goal of this method is to make a statistical approach using data from already produced machines. Nevertheless for new processes, expert knowledge is used to make an estimation.

Modeling the state of the machine and the possibility of a resulting failure Fig. 7 shows a simple model for the probabilistic dependency of the two categories. Furthermore the probability of a positive outcome of each process can be rated in dependency of the statistical state of the machine. This is modeled in the results of each process as shown in the lower part of Fig. 7.

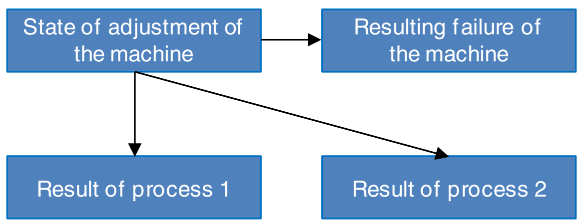

Fig. 7: Risk assessment of the machine state

Considering process heuristics as a tool to achieve an improvement for process duration and process quality, each heuristic can be applied individually as a process in the Bayesian Network. Thus, the possibility of assessing process heuristics with Bayesian Networks is given.

Through the application of expert knowledge the process map can be adapted to new requirements or to changes of process. On top of that for improvements concerning the state of the machine the presented method can cope with this change and display the impact instantaneously. Therefore, the influences with the highest impact on the throughput time can be identified and simulated.

5. Validation

The validation shows promising results at a company which is specialized on producing special machinery in the field of high power lasers. A reduction of the commissioning time by three days starting from nine days was shown by simply eliminating a commissioning process. On top of it by substituting the commissioning process with a process resulting from another strategy has shown a reduction of throughput time by almost six days. This was achieved even when the state of the process is judged very conservative. More failures than in reality existed were assumed.

Another positive effect of the Bayesian Network is that the probability of future quality losses and improvements can be modeled by changing the state of the machine. Thus, preventive approaches can be planned and simulated in advance.

In this case the method was applied to a commissioning process of a laser which will be integrated in a laser system. As process heuristics, the substitution of processes and the elimination of processes are applied (Fig. 8).

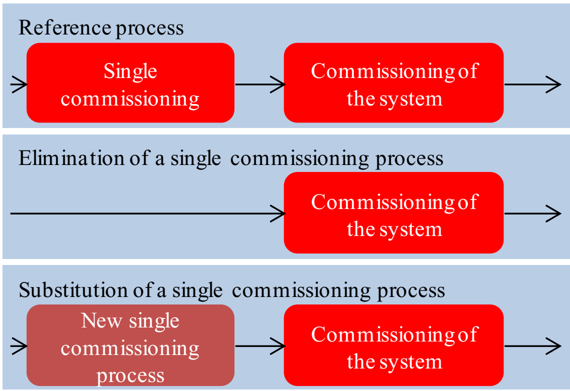

Fig. 8 Application of process heuristics on a reference process

In Fig. 9 the application of the developed method using the Bayesian Network is pictured. The upper two yellow boxes show the state of the machine and possible consequences in case of failures. For a better understanding, the matrix of production durations is divided into single red nodes. The two boxes below the blue box show the possibility of a good outcome of the commissioning process. Consequently, the times of a process in the case of failure and the case of success can be visualized. The blue box gives the possibility to make a process decision and to evaluate each option.

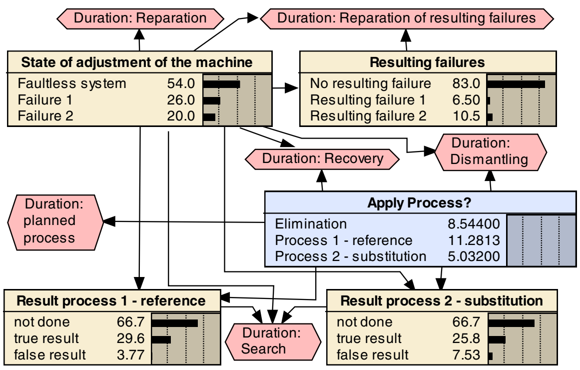

Fig. 9 Example of a Bayesian Network for estimating the throughput time

The pictured states of the machines result in a certain reliability of the executed processes. While the reference process has a higher reliability to show a true result, the substitution process needs much less time to execute. Thus the substitution process has a resulting duration involving all failures of less than half of the time compared to the reference process.

With this example process steps can be depicted. Therefore, the possibility is given to simulate all other process heuristics with this method.

6. Discussion

The proposed method is practicable in a wide field of application in the commissioning of special machinery. The input of valid data is necessary to achieve a realistic outcome. As not every detail about the production is known at the planning of the commissioning tasks, the prediction of future processes is affected. This means that the less knowledge is available, the farther the planned duration is differing from the actual necessary duration. In special machinery most companies have core competences in which they can make good predictions about the possible risks. But individual projects contain also less predictable tasks which make the estimation of the process duration more challenging and affect the approach presented in this paper.

The quality of the input data is crucial to the prediction of the process time. The given data origins on the one side from measured objective sources like the measurements of former process durations. On the other side processes have an origin from subjective sources like the expert knowledge needed to judge the risk of a new process. Thus, the prediction is influenced and possible deviations from the real process may occur. However the ability to connect expert knowledge with the objective data makes this method an efficient tool in the planning of the commissioning of special machinery.

Another point is the resulting variation in throughput time. The consequence of the time reduction because of a reduction of the commissioning to a certain extent can be a higher varying throughput time. Regarding a constant output quality, the alternative process of commissioning achieves different results compared to the original one. Therefore, the influence of process variations can for example affect certain customer supply dates. This happens because the method shows up the mean duration containing the average amount of failures and not the duration needed in this particular case. Nevertheless the duration without failures can be shown up by reducing the failure count in the box which resembles the machine state.

7. Summary and Outlook

In this paper the authors describe a method to reduce the duration of commissioning processes prior to the first application of the process. The approach is to combine expert knowledge and available data to make a statistical prediction of the planned throughput time.

The method to assess the risk and combine it with the throughput time estimation is shown in a validation case. The ability of certain processes to identify failures is modeled.

Furthermore, the existing throughput time can be analyzed by the method and adapted to a more efficient process. On top of that the simulation of different failure scenarios can be done by changing the state of the machine.

Existing approaches do not combine risk assessments and throughput time predictions. The proposed model combines both methods to achieve a realistic prediction. For a model with an even higher validity in further research the needed input data has to be qualified to get knowledge about the reliability of the method.

The paper presents the validation of the process heuristics elimination and substitution. Furthermore other process heuristics have to be validated to achieve an extensive validation. Nevertheless the theoretical validation for process heuristics was proved.

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