Simulation-enhanced decision-making in production logistics

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Abstract
The volatile environment today's manufacturing companies are facing generates pressure on decision-makers in production logistics. This is the reason why decision-making at the earliest point in time gains significance. The approach presented in this paper reveals how simulation tools can be used to bring forward the time of decision.

Keywords: Simulation, decision-making, production logistics

Introduction

Dynamic and high-competitive global markets ensure technological progress, but lead to an extremely unstable environment for production systems. Manufacturing companies in high-wage countries are increasingly challenged by lower production costs in low-wage countries (Brecher 2012). Beside high quality products, other key factors like delivery reliability can help to stay competitive. Therefore, high logistic performance on the basis of a well-planned and well-controlled production has never been more relevant than today (Schuh et al. 2013). Logistic performance as one strategic objective of a manufacturing company can be monitored on different levels of a production system, whereas key criteria are lead time, through-put, work in progress or capacity utilization (Gunasekaran et al. 2001).

The basis for adequate planning and control in production is information. Thus, information systems like Enterprise Resource Planning (ERP), Advanced Planning and Scheduling (APS) and Product Data Acquisition (PDA) have been established over the last decades. They help to plan and schedule on a short-, middle- or long-term-basis. However, in case of little changes or deviations during operation the existence of multiple systems often leads to incorrect, ambiguous or inconsistent data between systems which results in time delays and bad responsiveness within production control (Kwak and Kim 2012). Today, one consistent and up-to-date information system in terms of one product lifecycle management system is technologically realizable (Sääksvuori and Immonen 2008). It therefore needs to be established if production time and cost pressure occurs. This paper assumes the successful implementation of such an integrated information system which serves as basis for the virtual world.

The advantage of virtuality is its freedom from the constraints of time and place. Processes can be operated with nearly any speed and components can be freely transferred from one place to another. Virtual resources are unlimited and theoretically any number of experiments can be conducted in the virtual world with hardly any additional expense. Moreover, as simulations run in a fraction of a second, so-called virtual try-out can be realized in parallel and to physical processes without direct intervention (Takahashi 2011) (Verein Deutscher Ingenieure 2010). These cost and time advantages imply that virtuality and simulations have opened up a new world for production systems, whose potentials can be realized now, at times of high computing power and storage capacity. However, simulations mean first of all higher costs, as long as they do not result in a product or process improvement. Thus, we will analyze how simulations can contribute to leverage knowledge and improve decisions, and therefore optimize processes regarding production logistics. For this the decision-making process is considered and compare it with the possibilities of simulation environments.

The remainder of the paper is structured as follows. First, an overview of the state of the art concerning simulation procedures in production logistics on the one side and decision-making processes on the other side is given. After that both procedures are compared in order to find overlapping processes. The succeeding section presents a hypothesis regarding improvement of performance by simulation studies. The paper concludes with an outlook on potential research avenues.

State of the art

First applications of simulation technology in industrial plants began in the years of 1950 (Goldsman et al. 2010). Since then, manufacturing companies have benefited from the aid of simulation technology on three different levels: systems, controlling and kinematics (Kuehn 2006). As the application of simulations in planning, implementation and operation of technical systems increased, the Association of German Engineers (VDI) published the first draft of a guideline “Simulation of systems in materials handling, logistics and production” in 1993 in order to facilitate the entry of beginners into the application of simulations (Verein Deutscher Ingenieure 2013). It includes definitions, principles and requirements for simulation studies. Simulation development environments usually consist of the following components: simulation kernel, data management, user interface, and interfaces to external programs (Verein Deutscher Ingenieure 2010). The simulation kernel represents the model world including processing of events and coordination of individual components and is hence responsible as central sequence control system. The data management provides input, state and simulation results data in order to enable operating within a dynamic model. The entering of data and representation of results is realized by the user interface. The interfaces to external programs enable the integration of existing data inventories and the data transfer to other systems.

Simulation studies require a sequence of relevant steps which can be divided into preparation, implementation and evaluation (Verein Deutscher Ingenieure 2010). First, the preparation phase includes the formulation of the overall target profit maximization. It can be divided into eventually contradicting sub-targets, for instance delivery reliability, capacity utilization, through-put or minimizing work in progress. Second, the definition of tasks and modeling of interdependencies within the system are part of the preparation phase. After the development of a formal model is completed, it can be implemented into the simulation environment and experiments can be started. In the end the results of all conducted experiments require careful analyzis, so that adequate measures can be deduced. The basis for those processes is the gathering and preparation of raw data which can be conducted in parallel. Furthermore, the verification and validation of all phases’ results in terms of target, tasks, models or simulation results is essential in all phases of the simulation study. It serves to identify and eliminate errors as soon as they arise (Chung 2004). This involves careful documentation of each step and result of every phase. The common procedure for simulation studies is depicted in Figure 1.

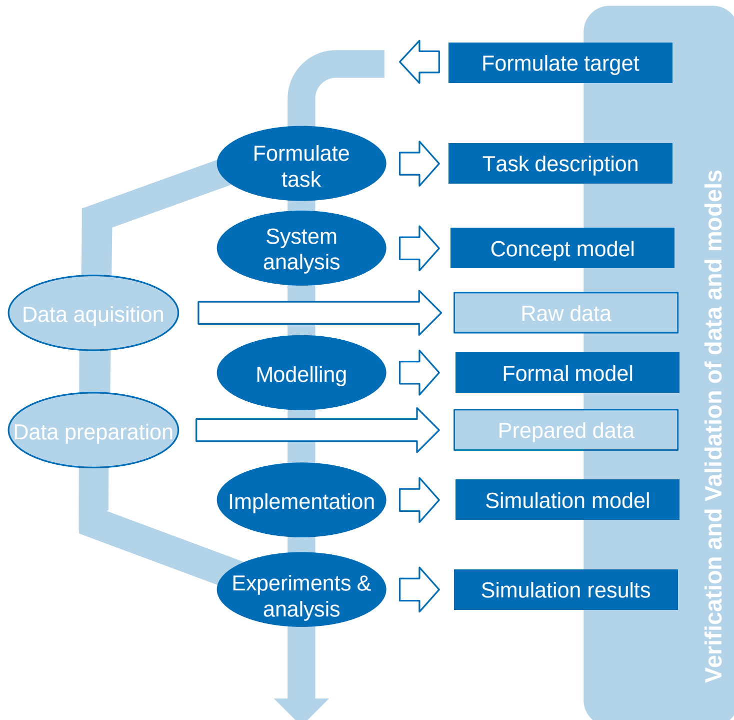

Figure 1: Procedure model for a simulation study (adapted from: Rabe et al. 2008)

Planning, implementation and operation processes permanently require decision-making. Thus, decision support systems (DSS) embedding simulations are increasingly deployed in such processes (Heilala et al. 2010). Before evaluating the effectiveness of embedded simulation technologies in DSS, it is necessary to understand the process of decision-making in planning. Bendixen and Kemmler (1972) define the following planning phases: problem identification, information analyzis, definition of interdependencies, identification of possible solutions, detailing problem-solving-concept, decision-making and implementation. For a better overview we cluster these phases into three main phases: preparation, decision-making and implementation, as summarized in Table 1.

Table 1: Decision-making process

Phases	**Process steps**
Preparation	1. Gather and filter information
	2. Understand and define relationships
	3. Identify and analyze alternatives
	4. Evaluate alternatives by criteria
Decision-making	5. Choose alternative
Implementation	6. Implement the decision
	7. Review the decision

Software-based DSS help to realize the tasks mentioned above, partly with or without the aid of humans, depending on the degree of automation (Chan et al. 2000) (Blutner et al. 2009). For decision-making itself, however, the human factor will remain essential, also in an Industrie 4.0-environment, respectively in cyber physical production systems (Schuh et al. 2014). But also the preparation of decision-making will always require the human factor, as will become clear in the following.

By comparing the simulation processes of Figure 1 with the preparation processes of Table 1 three main simulation study processes can be identified that are directly related to decision preparation, as depicted in Table 2. The storage of all simulation models, runs and results in the simulation database additionally serves as an efficient basis for decision-making.

Table 2: Decision preparation by simulation study and experience reservoir

Simulation study process	Equivalent decision preparation	Experience reservoir
1. Modeling	Understand and define relationships	Database
2. Experiments	Analyze alternatives	
3. Result analyzis	Evaluate alternatives by criteria	

First the modeling involves the definition and understanding of relationships within a system and results in a simulation model. On this basis, experiments can be simulated which serve to analyze alternatives. Consequently, the experiment results can be analyzed and visualized via so-called meta-models. After having identified the relationship between simulation study and decision-making the question arises to what extent the above described simulation processes can improve decisions or bring forward the time of decision. Therefore, a hypothesis is formulated in the following in order to reveal this effect.

Hypothesis

In times of increasing computing power it appears that focus is rather set on technical possibilities than on the principal matter. In terms of simulations this would mean that the preceding process, i.e. the modeling, and the succeeding process, i.e. the meta-modeling, are not intended to be neglected. Within the Cluster of Excellence “Integrative Production Technology for High-Wage Countries” of the RWTH Aachen University simulations are deployed both for logistics as well as on process level (Brecher 2012). In interviews with several workgroups it was stated that they primarily benefit from modeling. By investing considerable effort into modeling they better understand correlations within the system. Thus, they achieve high learning effects and consequently improve their planning or operating of physical processes.

This emphasizes that the benefit of simulation technology already begins with modeling and even before the first simulation experiment is conducted. Of course, simulation experiments also result in learning effects by revealing interactions between parameters and set targets as well as among parameters. After completion of the experiments, simulation results need to be interpreted and visualized via meta-modeling. Here the workgroups underlined again that the meta-modeling process involves learning effects by improving the understanding and interpretation of the effects of simulated alternatives. The guideline 3633 of the VDI underlines those statements: “Simulation thus supports the users in progressing from an understanding of the problem to an understanding of the system. On this basis, they can then comprehensively observe the system and finally find efficient measures to solve the problem.”

Therefore, we hypothesize that virtual modeling, simulation and meta-modeling are key enablers to faster improve the performance of physical processes via learning effects than with trial and error.

In Figure 2 the performance due to the working methods mentioned above is qualitatively drawn in form of learning curves to illustrate the hypothesis (Yelle 1979).

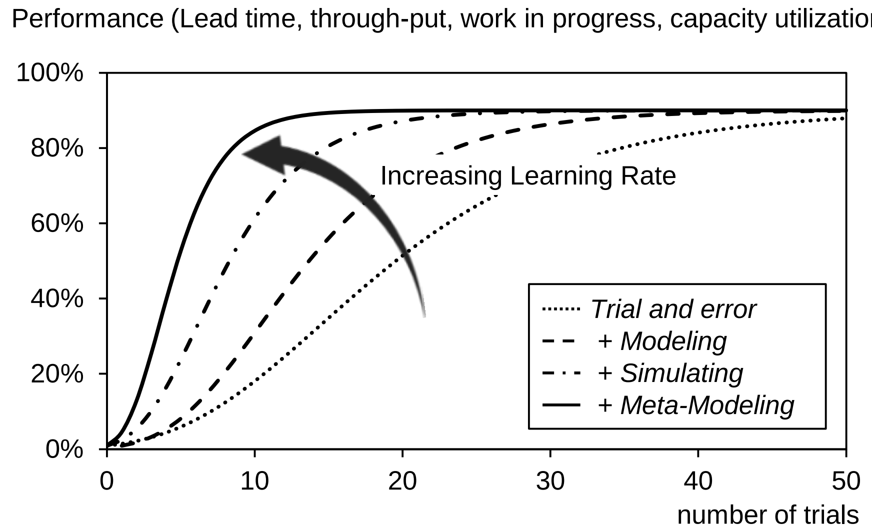

Figure 2: Learning curves of different working methods

Whereas the learning rate of the trial and error method is the lowest, modeling, simulating and meta-modeling lead to additional learning effects. The best learning effect is yielded, when all mentioned methods are deployed (black graph). The graphs depicted in Figure 2 emphasize an additive learning effect between the processes 'modeling', 'simulating' and 'meta-modeling'. This implies that the significance of a simulation study varies with the qualities of the underlying models. A simulation experiment, for instance, is only as good as the underlying model. Also the meta-model is only as good as the conducted simulation experiments. Finally, the decision-making will only have a valid fundament, if the underlying meta-model enables the conclusion of right coherences and visualizes usable information for the decision-maker. The corresponding function of the depicted graphs in Figure 2 is the following:

$$P(x) = a * (i)^{r^x} \tag{1}$$

where P(x) = Performance (Lead time, through-put, work in progress or capacity utilization)
a = Maximal performance
i = Initial performance due to prior experience
r = Rate parameter, theoretically related to working methods 'trial and error', 'modeling', 'simulating', 'meta-modeling'
x = Number of trials

The higher the learning rate, the faster the performance can be improved. Every performance improvement requires a decision of at least one parameter change. Thus, the increase of learning rate implies decision-making at an earlier point and therefore a time advantage. There is another factor that can reduce time in decision-making. This is described in equation 1 as initial performance due to prior experience and is related to the database of simulation environments that permanently stores updated models, simulation runs and improved meta-models. It keeps the knowledge level constant by "saving experience". By such an experience reservoir within a simulating system the decision basis is strengthened from the outset and performance can be directly improved. Those time reducing effects which lead to a quicker performance improvement are portrayed in Figure 3.

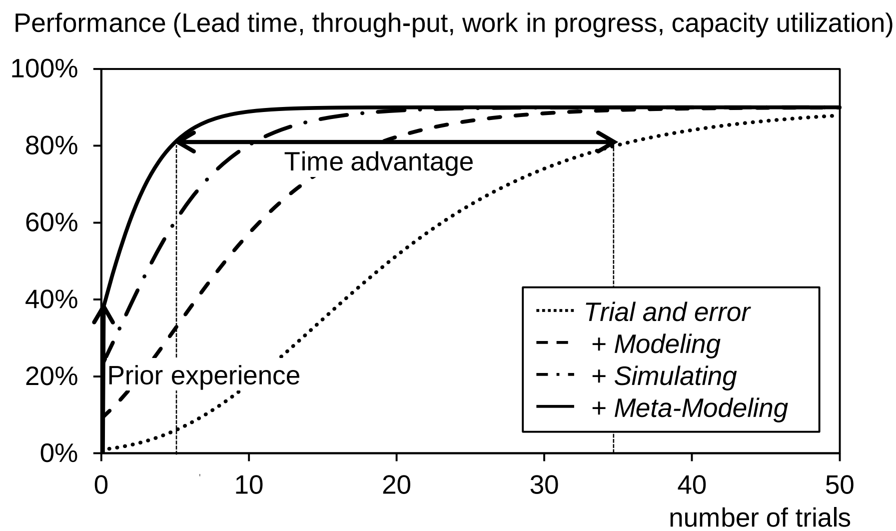

Figure 3: Accelerating performance improvement by working method and experience

Conclusion and future research

In this paper, the effects of simulation studies on decision-making in production logistics were presented. On the basis of conducted interviews within the Cluster of Excellence "Integrative Production Technology for High-Wage Countries", a hypothesis how simulation studies can contribute to improve performance in production logistics was formulated. Besides simulating, it sets the focus on modeling and meta-modeling in order to leverage learning effects and improve the decision basis. Future research needs to focus on the validation of the hypothesis. Also the quantification of the depicted learning curves needs to be addressed. Additionally, the results might be used to set criteria to evaluate existing simulation tools in production logistics.

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