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Simulating the benefit of disruption prevention in assembly

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Abstract

Purpose – The purpose of this paper is to investigate the benefit of pre-emptive disruption management measures for assembly systems towards the target dimension adherence to delivery times.

Design/methodology/approach – The research was conducted by creating simulation models for typical assembly systems and measuring its varying throughput times due to changes in their disruption profiles. Due to the variability of assembly systems, key influence factors were investigated and used as a foundation for the simulation setup. Additionally, a disruption profile for each simulated process was developed, using the established disruption categories material, information and capacity. The categories are described by statistical distributions, defining the interval between the disruptions and the disruption duration. By a statistical experiment plan, the effect of a reduced disruption potential onto the throughput time was investigated.

Findings – Pre-emptive disruption management is beneficial, but its benefit depends on the operated assembly system and its organisation form, such as line or group assembly. Measures have on average a higher beneficial impact on group assemblies than on line assemblies. Furthermore, it was proven that the benefit, in form of better adherence to delivery times, per reduced disruption potential has a declining character and approximates a distinct maximum.

Originality/value – Characterising the benefit of pre-emptive disruption management measures enables managers to use this concept in their daily production to minimise overall costs. Despite the hardly predictable influence of pre-emptive disruption measures, these research results can be implemented into a heuristic for efficiently choosing these measures.

Keywords Production, Simulation, Modelling, Manufacturing

Paper type Research paper

Introduction and motivation

Manufacturing companies face rising cost pressure due to increasing competition and production programme complexity. A main reason for this is globalisation, enabling especially new Asian companies to participate in the international market. In contrast to former times, not only immaculate deliveries and cost-efficient products are required for winning and keeping customers; furthermore, on-time delivery and flexibility are important to distinguish a company from its competitors (Womack *et al.*, 2007). Especially for durable

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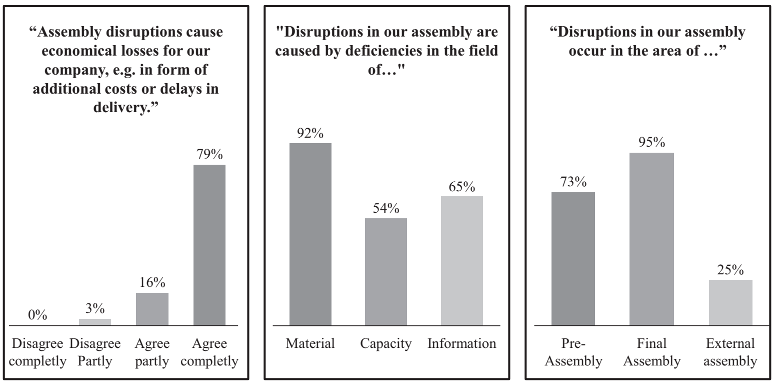
goods, on time delivery is essential, as late deliveries can lead to economic losses (Schuh *et al.*, 2013).

Assembly is the last value-adding process in the process chain of a manufacturing company and consumes a high proportion of the lead time and production costs (Petersen 2005). Avoiding assembly disruptions is vital for delivering on time and ensuring a cost-efficient production. The result of assembly disruptions, which lead to schedule instability and frequent process changes affecting the work atmosphere on the shop floor, are various economic losses. Activities like frequent rescheduling or other short-term measures can lead to tied up planning capacities (Wildemann 2015). As a result, successful disruption management is required in various industries (Yu and Qi 2004).

Various definitions of assembly disruptions exist. According to Eversheim, assembly disruptions can be defined as "every kind of unintentional deviation from the regular assembly process" (Eversheim 1992). According to Heil, disruptions consist of a quantity as well as a quality structure. The quantity structure defines how often a disruption occurs, while the quality structure refers to the disruption duration (Heil 1995). Various strategies to counter disruptions exist. The approaches can be divided into reactive strategies, which start after the occurrence of a disruption (Cauvin *et al.*, 2009) and pre-emptive strategies, which aim to prevent or minimise the impact of disruptions, even before they occur (Lehmann 1992; Kampker *et al.*, 2015). For pre-emptive disruption management, it is important to define up to which point measures have a positive benefit-effort ratio to achieve the highest on-time delivery rate (Yu and Qi 2004).

An empirical industry study, conducted in 2015 by the WZL of RWTH Aachen University, proves the high ongoing pertinence of disruption management, especially for low-volume assemblies. According to the study results, 95 per cent of the interviewed companies claim that they experience economic losses due to disruptions. Furthermore, the participating companies stated that a majority of the disruption causes can be clustered as material (92 per cent), information (65 per cent) or capacity (54 per cent) related. Additionally, the participants answered that disruptions are mainly located in final assembly (95 per cent) and pre-assemblies (73 per cent), just 25 per cent are located external of the assembly (Figure 1). The study participants rated pre-emptive disruption



Source: Wagner *et al.*, 2017

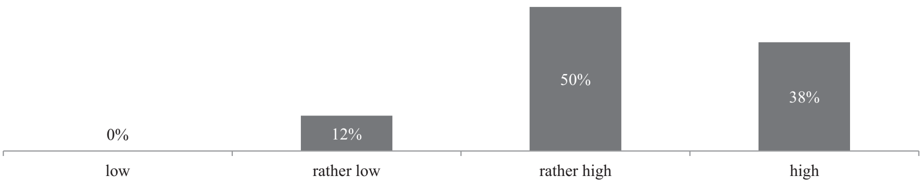
Figure 1. Evaluation of the potential of preventive disruption management in contrast to reactive disruption management

management with a higher cost saving potential compared with reactive disruption management. The results of the study are displayed in Figure 2.

As described, pre-emptive disruption management strategies aim to prevent or minimise the effect of disruptions before they occur. Therefore, they tend to offer higher benefits for an assembly system than reactive disruption management strategies (Heil 1995). Measuring the benefit of pre-emptive disruption management strategies is challenging and not yet solved, which therefore is addressed by this research using simulation models. Simulation models provide the option to model a complex, reality-based system in different conditions. The term simulation is defined in VDI norm 3633 as "Representation of a system with its dynamic processes in an experimental model to reach findings which are transferable to reality; in particular the processes are developed over time" (Verein Deutscher Ingenieure VDI, 2014). Using simulations enables the observation of the behaviour of complex or even non-existent systems, in various conditions (Zeigler *et al.*, 2010). In case of system uncertainty, these conditions, as well as the progress towards them, can be modelled either deterministically or stochastically. Depending on the demand, simulations are designed to progress either continuously or by discrete events, so they can be used to observe the system flow or the behaviour of the system in certain events, while using a minimal required time (Verein Deutscher Ingenieure VDI, 2014; Law and Kelton 2000).
Summarising, simulations can be used as an effective tool to investigate the disruption management behaviour of an assembly system. The long-term aim of the approach is to reduce the overall production costs by using purposeful investments to minimise disruption costs. A targeted examination of the benefit of pre-emptive disruption management by simulation models enables to control a high degree of uncertainty and complexity. Furthermore, it enables to investigate the system behaviour either for long durations or by the influence of different and even simultaneous disruption management measures as a single entity and in combination with each other.

Literature review on pre-emptive disruption management and simulation

A pre-emptive as well as a reactive approach for short-, medium- and long-term disruption management is provided by Eversheim. In his publication, the need for an efficient production information management system (PIMS) and Manufacturing Execution System (MES), which can recognise disruptions early, is claimed. The short- and medium-term disruption management focusses on recognising disruptions as soon as possible and reacts to these by mainly (re-)allocating capacities (i.e. staff, equipment, space) within the assembly. The long-term disruption management requires the organisational structures to define information flows for short- and medium-term disruption management. In this context, it also supports the prevention and faster recognition of disruptions by forming disruption regulation circles and continuous improvement of the disruption management processes. Finally, the disruption management is evaluated by an indicator system. The



Source: Wagner *et al.*, 2017

Figure 2.
Empirical study on disruption management

approach of Eversheim focuses on assembly and considers pre-emptive measures. Nevertheless, the quantitative benefit of chosen measures is not evaluated (Eversheim, 1992).

Lehmann creates a methodology to support the management of low-volume assembly systems when reacting to disruptions. He defines a disruption as every sort of unintentional deviation from the normal assembly and investigates the decision-making process and the conditions of disruptions in low-volume assemblies by using a literature review. As a result, Lehmann proposes to create a computer-aided support system, using the fuzzy-Petri net theory. The main tasks of the software are the determination and evaluation of different rescheduling options to minimise the impact of the disruption. Lehmann validates the approach and software on an ideal assembly system. In comparison to other approaches in research, Lehmann provides a user-orientated approach, using software tools. Nevertheless, the approach focusses on reactive disruption management and evaluates as well as minimises its efforts. Broadly, the achieved benefits are considered in a following case study (Lehmann, 1992).

Heil develops a comprehensive disruption management concept, which is applicable in various industries. Based on an empirical study, Heil defines a pre-emptive and source-oriented disruption strategy. He uses different quality management tools for analysing the source of a disruption. Based on this, Heil approximately suggests different actions but does not name any specific countermeasures. The main approach reallocates staff capacity and creates process standardisations as well as a visualised controlling. According to Heil, case studies have shown that pre-emptive disruption management is more beneficial than reactive disruption management. Nevertheless, specific measures and their benefits are not elaborated in detail (Heil, 1995).

Abumaizar and Svestka define disruptions as random subjects in a dynamic environment influencing job shop schedules. As examples for disruptions they use machine breakdowns, material delays, order rushes or cancellations. Abumaizar and Svestka's main aim is to minimise the rescheduling of job shops, meaning starting time deviations as well as sequence deviations. They develop a rescheduling algorithm, based on a binary machine activity tree, which addresses every process following an affected machine. It is identified whether a process is affected. If so, this process is rescheduled and the influence on the system is evaluated; if not, the process is not considered anymore. At the end, a performance measurement for the algorithm is conducted. The presented approach is an automated, reactive disruption management concept for parts production in job shops and can hardly be used for assembly systems. Furthermore, Abumaizar and Svestka focus only on the efforts and costs of the rescheduling, but they do not consider the resulting benefits of a pre-emptive approach (Abumaizar and Svestka, 1997).

Kleindorfer and Saad derive ten principles from a literature research to identify two key elements for disruption management. Therefore, their definition of disruption (risk) management includes operational risks, like equipment malfunction, unforeseen discontinuities as well as risks arising from natural hazards, terrorism and more. The first element of Kleindorfer and Saad's approach is the reduction of the frequency and severity of disruptions. The second element focuses on increasing the capacity to sustain/absorb disruptions without serious negative impacts. To create these elements, Kleindorfer and Saad demand special attention while designing a company's operating and managing structure. This approach mainly focuses on supply chain disruptions and is therefore just partly usable for assembly. Furthermore, the benefit of the two elements is not provided (Kleindorfer and Saad, 2005).

Qi *et al.* develop an approach considering the update of planned machine schedules due to random or anticipated disruptions. They define a disruption as the unavailability of a machine for some period of time. Following this, Qi *et al.* define that disruption management can be applied post-occurrence or preventive to disruptions. For both cases, they develop an optimisation model for the processing time of one machine schedule by using mathematical algorithms and theorems. Afterwards, they enlarge the scope to parallel machine schedules. Qi *et al.* mainly focus on achieving a different schedule with the lowest processing time, but without acknowledging other processes and products, which could also be affected in the system. Also Qi *et al.* do not consider the efforts to implement measures or the benefit of pre-emptive measures. The approach could partly be used for disruption management in assembly systems (Qi *et al.*, 2006).

Liu *et al.* develop a model for airline operations using a computer-aided inequality-based multi-objective genetic algorithm. The very complex and difficult environment of the airline industry leads to deviations in the planned schedule, which are caused by various reasons. The model requires hard and soft constraints to compare different solving algorithms. Hard constraints address basic system criteria which cannot be changed. Soft constraints consider attributes changed by the disruptions. The model seeks for a pareto-optimal set for the flight schedule which supports the decision makers. *Liu et al.* validate the model using actual airline flight schedules. Due to the specific focus on the airline industry, the approach is hardly transferable to assembly systems. Furthermore, the model is designed for reactive disruption management and approximately considers the benefit of disruption management (Liu *et al.*, 2008).

Schmitt and Singh develop a computer-aided model for supply chain disruption management. The model is based on two types of simulations. First, a Monte-Carlo simulation model for assessing the disruption risk profiles for locations as well as the connections inside the supply chain. Second, a discrete-event simulation model for the material flow and network interactions in the real-life supply chain is created. Considering both simulations, Schmitt and Singh show the impact of disruptions and mitigation strategies on the system. The complete model was used to run experiments with hypothetic disruptions and measure their influence on the supply chain, focusing on the system's recovery time and fill rate. The approach shows the strength of computer-aided disruption management. Their concept is designed for supply chains and needs to be adopted to be usable for assembly systems. Schmitt and Singh do not mention the type and effect of mitigations they suggest to implement (Schmitt and Singh, 2009).

The approach of Cauvin *et al.* focusses on minimising the effects of disruptions in corporations. Cauvin *et al.* define disruption as an unanticipated event, caused by uncertainty of the environment, which influences pre-established controlling processes. The research claims that existing disruption management approaches do not take the position of the actors in distributed companies into consideration. The reaction time and the system impact are used as evaluation criteria in Cauvin *et al.*'s work. After a preliminary analysis, they develop a cooperative approach, treating the actor problem like a supply chain problem, using supply chain disruption management measures. Based on a multi-agent model, Cauvin *et al.* develop a simulation model for the decision process of all actors, which mainly creates transparency for the process and evaluates the pertinence of chosen solutions. The approach focusses on the decision process after a disruption appeared. Therefore, it does not consider any pre-emptive measures and strategies. The benefit of disruption management is not considered, but the approach is applicable to assemblies (Cauvin *et al.*, 2009).

Approach for determining the benefit of pre-emptive disruption management

The approach for determining the benefit of pre-emptive disruption management is based on creating an assembly model and simulating the behaviour of the system under the influence of different disruptions. VDI norm 3633 is used as a foundation for the simulation creation, regarding the basic simulation structure and particular creation steps. The approach is split into three phases. First, the simulation model creation phase, followed by the experiment preparation and operation phase and finally the result evaluation and display phase. During all three phases, a verification and validation process is applied to every step of the approach. The complete approach is displayed in Figure 3 and is subsequently explained in detail.

Simulation model creation

The simulation model creation is the first step and consists of three sub-steps. First, an assembly system is designed for the simulation model. As the approach shall be generally applicable and independent of the simulation software, the simulation model needs to be a simplified and reduced version of a potential and representative real-life assembly system. This is also a general requirement for using simulation methods. Therefore, all elements, which can occur in an assembly system should be implemented and modelled close to reality, completely and coherently. The foundation for the assembly system design is the long-term project experience of the authors, especially in low-volume assemblies, which is used in every following design step. The assembly system framework is fixed, before the system design is detailed. The system design is operated using Petri nets. These have several advantages, like ease of modelling of complex systems, good form of visualisation, ease to recognise dead locks, ease to derive steering algorithms and discrete event simulation models, and existing modelling approaches for flexible manufacturing systems can be used (Zhou and Venkatesh 2000). For developing the simulation models the five-step procedure for applying Petri nets in manufacturing system design of Zhou and Venkatesh is used as methodology. Furthermore, the main framework assumption is the usage of different organisational forms. Two detached simulation models are created, on the one hand a group

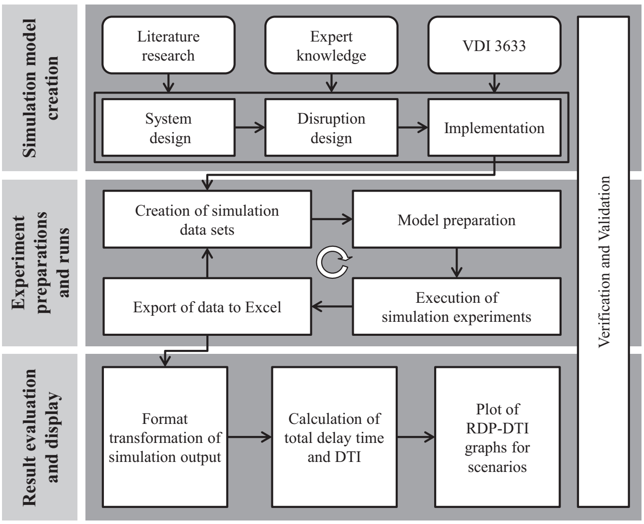


Figure 3. Approach for determining the benefit of pre-emptive disruption management

assembly, on the other hand a line assembly, with the aim of proving the different behaviour towards disruptions and measures. Group assemblies have more inherent absorption capabilities, which reduce the effects of disruptions to a certain degree. Line assemblies are fixed, regarding their absorption capabilities, to the number of processes of one station and the tact time (Wagner *et al.*, 2015; Lehmann 1992). Additionally, the assembly system's main characteristics are determined. Both models produce two products, with high process communality, each product having a cycle time of 280 h and 24 processes. Each process is modelled having a specific production time for each product as well as a distinct number of predecessors and successors. Furthermore, system inherent absorption capabilities are implemented as a decreasing effect of disruptions, based on the ideas of Wagner *et al.* In their research, buffer times, process flexibility and operating time flexibility are defined as main absorption capabilities (Wagner *et al.*, 2015). In the end, of the assembly system design, a pseudo code for both systems is created to ensure the model's completeness, validity and programming feasibility. A pseudo code is a visualisation of the designed assembly systems, using simplified software code and models (Verein Deutscher Ingenieure VDI, 2014; Rabe *et al.*, 2008).

As second step, the discrete disruptions in the assembly system are designed. Therefore, the concept of disruption potential (DP) is developed (Figure 4), based on the pre-work of Wagner *et al.* (Wagner *et al.*, 2015). It is set as equivalent for each process in the assembly system. The design of the DP is based on disruption categories, which need to be differentiated, as well as a specific disruption profile for each category.

According to Heil, a single disruption consists of two aspects: the disruption severity and the disruption threat (Heil 1995). The disruption severity represents the impact of occurring disruptions and is influenced by the system's absorption capability, which was already introduced beforehand, and the structural effect of assembly factor. The disruption threat is used to determine the likelihood of a disruption's occurrence and depends on structural assembly factors as well as historical data.

In the simulation model, the disruption threat represents the intervals between two disruptions, while the disruption severity is embodied by the disruption duration. Probability distributions are used for their parametrisation. Possible probability distributions, based on existing failure and reliability models, are the negative exponential (Negexp), the Weibull, the logarithmic normal (Lognorm) and the Erlang distribution (Law and Kelton 2000).

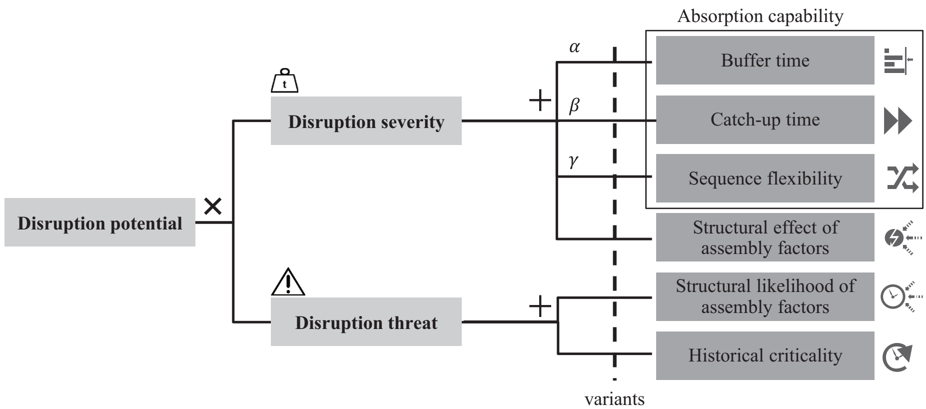


Figure 4.
Composition of the disruption potential

For the disruption threat, the Negexp and the Weibull distribution are considered. The Negexp distribution is commonly used in failure models to represent the time between independent events, occurring at constant rates or the lifetime of devices. The Weibull distribution is mainly used in reliability models to determine the lifetime of devices or time to failure. In practice, both distributions create significantly different results and are both commonly used to represent the interval of disruptions. For this reason, both distributions are used for the simulation experiments. During the conclusion and result interpretation, the effect and usability of both distributions will be further discussed based on the simulated results (Law and Kelton, 2000).

The disruption severity can be modelled, by using either a Lognorm or an Erlang distribution. Both functions are used for modelling the time to perform a task and as an approximate estimation in the absence of data. The main difference between both distributions is the likelihood of the expectancy value as well as the gradient for small and high values. Experiments show that the results for both probability distributions do not vary significantly. The more distinct expectancy value as well as the smaller likelihood for short disruption durations of the Lognorm distribution are, in contrast to the Erlang distribution, the criteria for choosing the Lognorm distribution (Law and Kelton, 2000).

In the last step of the disruption design, all probability distributions are parametrised. In assemblies, disruptions occur causing problems in various areas and often the cause of a disruption and the physical appearance vary. An empirical study of Lehmann showed that industry companies experience various disruptions. Therefore, Lehmann considered all occurring disruptions of a real-life assembly system and categorised them into in the three categories Material disruptions with a proportion of 63 per cent, information disruptions (19 per cent) and capacity disruptions (18 per cent) (Lehmann 1992). Each category contains various possible disruption causes, which can be addressed by different countermeasures. Due to the possibility of measures addressing one or more disruption categories, each category is implemented into the simulation model independently, having unique interval and duration parameters. Furthermore, Lehmann discovered that 25 per cent of all processes, in operating assembly systems, are disrupted and 22 per cent of all produced goods are finished delayed. These figures are used to calculate an expectancy value for the general disruption threat. The value is defined as the quotient of the cycle time and the percentage of disrupted processes. Derived from this value, the expectancy value for each category is customised according to its occurrence likelihood, to create the category specific expectancy value. The disruption severity needs to be parametrised by a mean value as well as a scattering value. Lehmann's empirical study showed that disruptions last in average four hours, with a minimum of several seconds and a maximum of 12 days (Lehmann 1992). These values are common for all three categories as no differentiations are mentioned in literature or by industry.

Finally, after the assembly system and the disruption design are finished, both need to be implemented into a simulation tool. Various tools are existing to implement the simulation, whereas the decision for a specific tool is not influencing the simulation results. As the simulation model has been set up as a Petri net Model, a fundamental requirement for simulation is the suitable for Petri nets or even actively supports them. Due to this, the software Tecnomatics Plant Simulation 10 is instrumented for this use case, being based on Petri nets. Additionally, plant simulation offers pre-defined assembly modules and connectors along with an option to include disruptions into each module. Reasons for the specific used software are the process flexibility, the system in- and output logic as well as the start and end time measurement were implemented by self-written methods which were easily implementable. Additionally, the software offers pre-defined probability distributions usable for the use case. After the setup of the model, a verification and validation process, regarding correctness and fulfilment of all requirements, are operated.

In Figure 5, an overview of the used simulation model for the organisational form line assembly is presented. Five tacts are arranged in a row, each having a specific substructure representing the processes of the tact. Each process has a table, which includes its process time for each product variant, and up to three steering methods in case of product entrance, disruption or product exit.

Experiments preparations and runs

The second phase of the research is the experiment preparation and run. In the beginning, the number of planned experiments and their corresponding input data are defined. As result of the simulation, the influence of different disruption profiles on the assembly system should be displayed. Therefore, the beforehand introduced disruption potential (DP) is used as an indicator for the influence. The DP, comprising the disruption severity (c_S), the disruption threat (c_T) and their sub-categories, called criticality factors, are formalised in equation (1).

$$
\begin{aligned}
DP(a_i) &= c_S \cdot c_T = \frac{1}{2} \cdot (c_O + c_E) \cdot \frac{1}{2}(c_L + c_H + \varepsilon) \\
&= \frac{1}{2}(\alpha \cdot c_B + \beta \cdot c_C + \gamma \cdot c_F + c_E) \cdot \frac{1}{2}(c_L + c_H + \varepsilon) \qquad (1)
\end{aligned}
$$

$DP(a_i)$ = Disruption potential
a_i = Investigated assembly process i
c_S = Disruption severity
c_T = Disruption threat
c_O = Offset capability
c_E = Structural effect of assembly factors

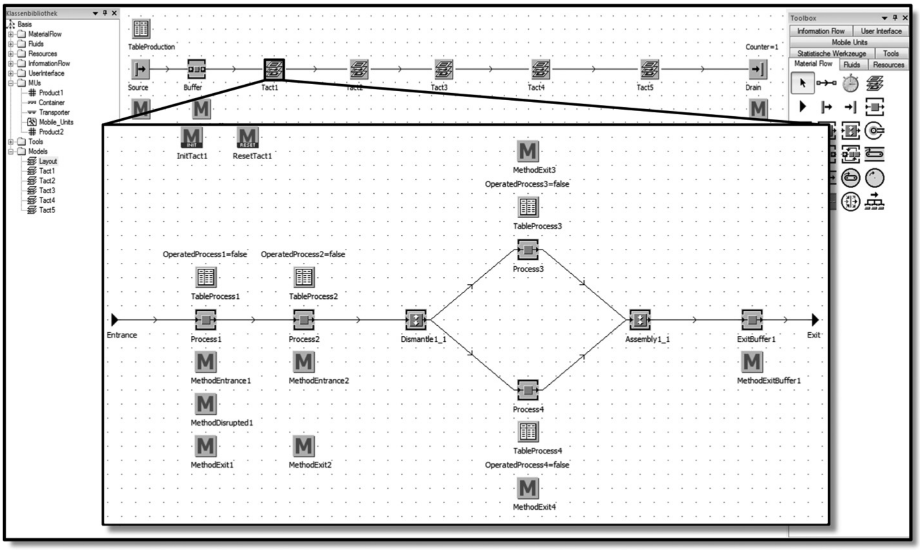


Figure 5.
Screenshot plant simulation: line assembly simulation system

c_L = Structural likelihood of assembly factors
c_H = Historical criticality
c_B = Buffer time
c_C = Catch-up potential
c_F = Process flexibility
α, β, γ = Weighing factors
ε = Basic likelihood

In practical usage, single disruption management measures are selected to address certain problems. The research presented here does not evaluate the benefit of single measures, but of the overall disruption management, independently from a specific single measure. Therefore, the aspects of the system, which are influenced by disruption measures, were identified. The specific measure selection has to be based on practical experience and will be operatively described following. Therefore, also results and experience from former research with a medium-sized German enterprise, producing special equipment for the mining industry, e.g. large-scale pumps, are used to develop a relative factor for comparing disruption management measures and reproducing the measures' behaviour in the simulation model.

A specific pre-emptive disruption measure either has an influence on a single process or on several processes of the assembly system. For example, additional equipment influences the process it is used in, while additional qualification of employees can influence several processes at the same time. The influence on the different disruption categories of a measure varies depending on the specific measure. Some measures have a dedicated influence on one category, while others address several categories at once. The impact of pre-emptive disruption measures can be distinguished in three impact areas. The impact of a specific measure can target the disruption threat, the disruption severity or both at the same time. Therefore, the impact of a specific measure changes at least one criticality factor, which can be observed in the change of the disruption potential of one or several processes.

To implement these four aspects into the simulation model, a characteristic factor, named the relative reduced disruption potential (RDP), is developed [equation (2)-equation (5)]. This factor is defined as the relative difference of a disruption potential before and after a measure is implemented per disruption potential before measures. The RDP is independent from specific measures, displays the measure's influence onto a single process or the assembly system and can easily be varied. The RDP has a pre-defined range from zero to one and is applied to all processes in the simulation model simultaneously. A single simulation run for a specific RDP is defined as one experiment, addressing a specific measure influence and measure impact. The combination of one experiment with varying probability distribution parameters forms a data set. Each potential combination of the three factors is created, forming an experiment with corresponding data sets. RDP variations are, despite assembly reality, applied to all processes of the simulation model at once. The additional complexity of single process RDP variations and all possible process combinations are not representable as part of this research. In the simulation model, the RDP is implemented as change of the probability function parameters (Table I).

After all data sets are created, operation cycles for the simulation models are started. First, the simulation model and the output data files are prepared. The used data files are not real-world data. Nevertheless, the basis of the simulation data sets is estranged industry values, which could not be used due confidentiality reasons. The used data were cross-checked with project data from various industry research projects at the Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University. The model preparation included the transfer and implementation of new data sets, the reset of

Table I.
Calculations for the different constellations of RDP

RDP	Process i		System s	
Single measure	$\mathrm{RDP}_{\mathrm{i,m}} = \frac{\mathrm{DP}_{\mathrm{prior,m,i}} - \mathrm{DP}_{\mathrm{after,m,i}}}{\mathrm{DP}_{\mathrm{prior,m,i}}}$	Equation (2)	$\mathrm{RDP}_{\mathrm{s,m}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \left(\mathrm{DP}_{\mathrm{prior,m,i}} - \mathrm{DP}_{\mathrm{after,m,i}}\right)}{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{DP}_{\mathrm{prior,m,i}}}$	Equation (3)
Measure combination	$\mathrm{RDP}_{\mathrm{i,MC}} = \omega \cdot \sum_{\mathrm{m}} \mathrm{RDP}_{\mathrm{i,m}}$	Equation (4)	$\mathrm{RDP}_{\mathrm{s,MC}} = \omega \cdot \sum_{\mathrm{m}} \mathrm{RDP}_{\mathrm{s,m}}$	Equation (5)
	i	Assembly process	m	Prevention measure
	s	Assembly system	MC	Measure combination
	$\mathrm{DP}_{\mathrm{prior,m,i}}$	Disruption potential prior to implementation of a prevention measure m	$\mathrm{DP}_{\mathrm{after,m,i}}$	Disruption potential after implementation of a prevention measure m
	$\mathrm{RDP}_{\mathrm{i,m}}$	Reduced disruption potential of measure m in process i	$\mathrm{RDP}_{\mathrm{s,m}}$	Reduced disruption potential of a measure m in the entire assembly system
	$\mathrm{RDP}_{\mathrm{i,MC}}$	Reduced disruption potential of the combination of measures in process i	$\mathrm{RDP}_{\mathrm{s,MC}}$	Reduced disruption potential of the combination of measures in the entire assembly system
	Ω	Redundancy factor [0, 1]	n	Amount of assembly processes

the software tool from beforehand simulation runs and the verification of the correct setup of the model. Afterwards, the simulation is executed for the prepared experiments. A simulation run for a specific experiment has a production period of one calendar year, with five working days per week, with two 8-h shifts a day. During each experiment run, around 150 products are produced. The minimal amount of products produced in each simulation model is determined by the amount of products being produced without any pre-emptive measures applied, which equals a system with an RDP of zero. The maximal amount of products is realised in a simulation run with a system without any disruptions, equalling an RDP of one. For evaluation and comparison reasons, just the throughput-times of the minimal amount of products are used. All additional products can be seen as additional benefit by the pre-emptive disruption measures. Subsequently, the simulation results are transferred to a spreadsheet for later evaluation. The three simulation operation steps are repeated, until all experiments are operated successfully.

Result evaluation and display

In the beginning, the transferred simulation result data are formatted. The data are changed from time stamp data, meaning start and finish dates of one specific product during an experiment, into a single value displaying the total production time of a product. The total production time is defined as the time span between the entry of the product into the assembly system, symbolised by the product creation point in the simulation, and the product handover after the assembly is finished, symbolised by the drain at the end of the simulation. Afterwards, each total production time is compared to a corresponding "ideal" reference production time. The reference production time is defined as production time without any disruptions in the assembly system. The time difference between the simulated production time and the reference production time is the delay time. The sum of the delay times for all produced products is the total delay time for an experiment run. To be able to compare the total delay times, the relative disruption time improvement (DTI) is created [equation (6)]. This variable describes the relative improvement of the disruption time, based on the maximum of all total delay times. The maximum of the total delay time is calculated by having disruptions of all categories and an RDP of 0 in every category.

$$\begin{aligned} DTI_m &= \frac{t_{D,s,max} - t_{D,s,m}}{t_{D,s,max}} \\ t_{D,s} &= \sum_{i=1}^{n} t_{D,i} \end{aligned} \tag{6}$$

DTI_m = Relative reduced disruption potential by a certain measure
$t_{D,s,max}$ = Total delay time in the system without preventive measures
$t_{D,s,m}$ = Total delay time in the system with preventive-measure
$t_{D,i}$ = Delay time in process i
i = Assembly process
s = Assembly system
m = Prevention measure

Translating the simulation results into assembly practice and management recommendations

The DTIs are first calculated and afterwards plotted for a set of corresponding experiments. A set of corresponding experiments is defined as all experiments sharing a disruption category or a specific disruption category combination. Each plot displays the RDP change on its x-axis, the corresponding DTI change on the y-axis and all related curves for the organisational form as well as disruption category. The visualisation enables an easier comparison of the simulation results of different categories and category combinations with each other to pinpoint the differences of disruption severity and disruption threat behaviour as well as the different probability distributions. Exemplary, the visualisations for the single disruption category combinations of group assembly as well as the material disruption category of line assembly are presented, each using the Weibull–Lognorm distribution combination, in Figure 6.

The diagrams A, C and D show the results for pre-emptive measures addressing each one of the three disruption categories material, information and capacity. Both top diagrams display the disruption category material for the group assembly (A) and for the line assembly (B) simulation models.

All curves, which are created within the validation of this approach, are representing an ideal system state. They cannot represent a real production system in any way. Rather the guideline of the approach is to create a parametrisation of the disruption management for a specific assembly system. The approach is developed in an industry-close research environment using expertise from real-life to create the simulation systems as well as the simulation context. The following observations can therefore be applied directly to low-industry assemblies in general.

General observations were investigated, which occur in all diagrams, independently of the organisational form, the probability functions and the disruption categories. Not a single curve achieves a DTI of one, as shown in Figure 6. A DTI of one equals a system without any delay, which is the theoretical optimum of assembly systems. If the RDP value rises, the

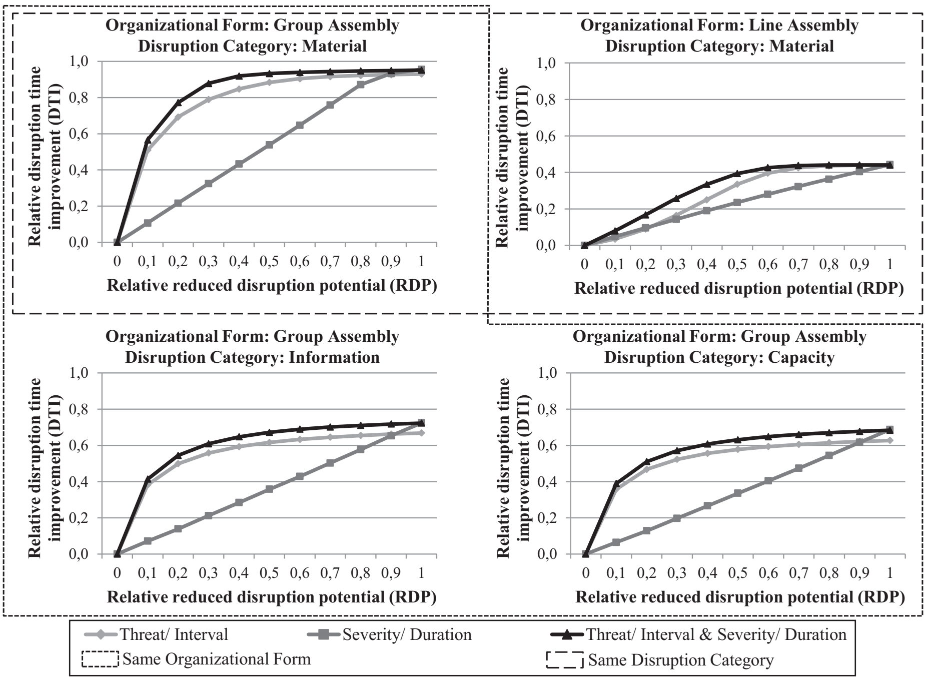


Figure 6.
Plotted simulation results using the Weibull probability function

probability function parameters for the disruption threat increase as well, causing an increasing DTI. The probability function parameters for the disruption severity decrease for an increasing RDP, but do not reach a value of zero, due to the minimum of the severity probability function being incrementally higher than zero. A decrease of the probability function parameters of the disruption severity leads to an increasing DTI. This causes the disruption still being possible, but more unlikely than before. The conducted research supports this statement. Consequently, an effective combination of pre-emptive and reactive disruption management for assembly systems to cover most disruptions needs to be targeted. Furthermore, not all DTI curves approximate a unique maximum DTI; moreover, their maximum values vary significantly around the maximum. Various reasons are possible for explaining why each curve has an independent maximum. One reason is the combination of its unique parameters and another the result of the independent experiment runs, which consist of an individual, randomised production programme.

Pre-defined variation characteristics are investigated regarding their influences on the simulation results. The differences between the used organisational forms are examined as presented in both top diagrams in Figure 6. The DTIs of the group assembly curves (A, C) have a higher maximum than the line assembly (B, D) DTI curves. Furthermore, the group assembly system shows a significantly lower amount of total delay time in all scenarios. Both behaviours can be explained by the higher absorption capabilities of a group assembly. The tact restrictions of line assemblies, in form of fixed tact times and a limited process flexibility, constrain the positive system-wide effects of pre-emptive measures. Nevertheless, no evidence proves that line assemblies or group assemblies require disruption management to a different extent.

The differences in the results of the used probability distributions are investigated next. Both distributions show equal curve behaviours for the same input parameters. The results of the Weibull function display higher DTI maxima with less scattering between the different curves. In contrast, the Negexp function has a more consistent behaviour with fewer outliners in its values. Exceptions are the results of the combination of all three categories, having the line assembly as organisational form and using Negexp probability function. Only the curves which RDP changes have an impact on the material disruption duration and do not have an impact on the material disruption interval, have an S-shaped progression. The S-shape is the least beneficial shape and represents a high RDP demand for small DTI improvements and high impacts of high RDPs on the DTI. This leads to the statement that in these scenarios pre-emptive disruption management is just beneficial when implemented to a high degree. The occurrence of this specific behaviour was unexpected and will be addressed in further research. Irrespective of this phenomenon, a general recommendation, which probability function to choose in future modelling and application, is hardly possible. For using the simulation results in a real-life purpose, the used probability functions need be defined for each specific case, depending on the system restrictions and demands of the specific use case. For an exemplary usage of the simulation results during this research, the Weibull function is used and is further recommended due to the fewer scattering and less outliners.

Comparing the behaviour of the two corresponding curves with equal parameters but different categories/category combinations, independently of the used disruption probability function, material-related curves achieve higher maximum DTIs in comparison to information and capacity-related curves. Comparing the A C and D diagrams in Figure 6, this behaviour can be observed. Comparing curves, which address several categories at once, shows that simulation experiments containing the disruption category material achieve a higher maximum DTI than experiments without material disruption reduction, independently of the reduced disruption impact area. This behaviour can be explained by the parametrisation of the disruption probability functions based on the input data of the model. According to Lehmann, the likelihood for a material-related disruption is approximately three times higher than for information and capacity-related disruptions. This input was used to parametrise the probability functions. The behaviour shows that the designed disruptions as well as the programmed integration in the simulation model are valid and represent the pre-defined input correctly.

Regarding the impact of disruption management measures, different curve shapes are displayed in the simulation result plots (Figure 6). The disruption threat/interval curve is, independent of the disruption category, characterised by a concave shape, while the disruption severity/duration mainly has a linear shape. A concave shape has a high gradient and approaches its maximum early, whereas a linear shape represents a constant relation between RDP and DTI, reaching its maximum later than concave-shaped curves. Furthermore, combinations of disruption severity and disruption threat have a progression in between these two extremities. Regarding pre-emptive disruption management, a concave-shaped behaviour is more beneficial for small RDP values due to a higher DTI per RDP. This leads to a higher benefit per input for small RDP (<0.5) changes and minimal DTI increases for high RDPs (>0.5). RDP in general is transformable into efforts, such as time or money. As result of the different curve behaviours, measures influencing disruption impacts at the same time are most beneficial. Furthermore, measures influencing the disruption threat, meaning the interval of disruptions, are more beneficial than measures influencing the disruption severity, and are to be prioritised.

To sum up the results of this research, it can be said that pre-emptive disruption management leads to significant improvements of the output of assembly systems. Reducing the total disruption time leads, independently of the organisational form and the disruption profile, to an improved on-time delivery rate. Generally, the reduction of the disruption threat is more beneficial than the reduction of the disruption severity. Furthermore, the initial reduction of delay times (DTI) is achievable by small RDPs, whereas the reduction of the remaining delay times requires higher RDPs. In general, a reduction to zero delay times is only theoretically possible. Additionally, it has been shown unilateral implementation of pre-emptive disruption management does not lead to optimal results; rather a combination with reactive disruption management is required.

The method is a heuristic, as no guarantee for an optimal benefit-cost ratio in pre-emptive disruption management can be promised, thus the method is not described as an optimisation algorithm. As for all heuristics, the aim is to gain good results with limited data and in a short range of time with low costs of applying the method.

Application of the research results

The research results are implemented into an overall heuristic for an economic selection of pre-emptive disruption management measures (Burggraef *et al.*, 2017). This simulation research delivers the benefit calculation for disruption countermeasures as well as for measure combinations. A specific, measure-related RDP is calculated by evaluating the effect of the measure onto a real-life assembly system. The resulting RDP is used to determine the corresponding DTI value by linear interpolation between the two simulated RDP-DTI experiment combinations. Based on the DTI and a separate cost estimation, an effort-benefit ratio is calculated, which is used for ranking several specific measures and measure combinations. This process should be implemented into an IT tool, supporting the decision maker as well as reducing the management costs of the approach significantly. The requirements towards such an IT tool are developed in further research following this paper.

Conclusion and outlook onto further research

This research proved that pre-emptive disruption management is a beneficial approach for the use in assembly environments. Nevertheless, pre-emptive disruption management in general cannot ensure a disruption free assembly environment and would not be cost efficient. A solution for this is a combined disruption management to encounter disruptions preventively, before they can occur, until a cost-efficient break-even point as well as reactively after they occurred, in the cases in which preventive disruption management was unsuccessful or not in place. Various influence factors have an effect on the beneficial behaviour of pre-emptive disruption management. The organisational form of an assembly system was determined as one main factor, showing that pre-emptive disruption management for group assemblies is more effective than for line assemblies. Other influence factors are the category and the impact of the disruptions themselves as well as the system inherent absorption capabilities of an assembly system.

The approach of using simulation for characterising the benefit of disruption management is in general proven being an effective evaluation way. The simulation approach enables to compress the complexity of an assembly system into an applicable model, which delivers feasible and coherent results. Additionally, complex research fields, like pre-emptive disruption management, which are not observable in real-life systems due to their hypothetic character, can be modelled by simulation methods. Even for assembly systems, which lead to a model with a high degree of uncertainty, many assumptions and poor data quality simulation methods are applicable, whereas the result quality needs to be verified for each case individually. Especially for this research question, with no real-life data available, the uncertainty could either be solved by literature input or at least be decreased by the usage of two independent solutions to determine the influence of the uncertainty. As an example, the usage of two different probability functions for describing the disruption threat can be named. Furthermore, the result reproducibility proves the validity of the model as well as its modelled components. Finally, the possibility to easily vary and adopt the simulation's input parameters with minimal effort and costs is beneficial for research approaches as well as industry approaches. This enables a comprehensive examination of the research problem and is a basic requirement for an industrial usage of pre-emptive disruption management.

This research is the continuation of previous studies in the area of disruption management. As succession to this study, further research will be applied to this area. Especially for the benefit of pre-emptive disruption management, more experiment variations as well as other assembly models will be operated for a further understanding of pre-emptive disruption management. A study of RDP changes for single processes or individual process combinations will help to understand the difference between process and system influences of disruption management. Furthermore, the simulation of an industry-sector specific, real-life assembly system is planned to define, which processes need to be focussed by pre-emptive disruption management in specific industries. Simulating a different assembly model could also be used as additional result validation for this study's results and can provide additional understanding about the influence of different assembly parameters onto the benefit of pre-emptive disruption management. In addition, the application of the used research data into a different simulation software can be done to verify the result independence from the used software.

Parallel to this research a methodology for choosing cost-efficient pre-emptive disruption measures was developed and connected to this approach. Both implemented into a comprehensive IT tool enable a on the one hand to increase the daily usability of the approach and on the other hand to decrease the management costs of the approach. Savings are achieved by changing the disruption management costs structure from short-term costs to predictable long-term production investments.

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