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PERFORMANCE IMPROVEMENTS IN HORIZONTALLY INTEGRATED PRODUCTION NETWORKS THROUGH REAL-TIME RESCHEDULING IN THE EVENT OF DISRUPTIONS

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Abstract

Rescheduling is a frequently used reactive strategy in order to limit the effects of disruptions on throughput times in multi-stage production processes. However, organizational deficits often cause delays in the information on disruptions, so rescheduling cannot limit disruption effects on throughput times optimally. Our approach strives for an investigation of possible performance improvements in multi-stage production processes enabled by real-time rescheduling in the event of disruptions. We developed a methodology whereby we could measure these possible performance improvements. For this purpose, we created and implemented a simulation model of a multi-stage production process. We defined system parameters and varied factors according to our experiment design, such as information delay, lot sizes and disruption durations. The simulation results were plotted and evaluated using DoE methodology. Dependent on the factor settings, we were able to prove large improvements by real-time rescheduling regarding the absorption of disruption effects in our experiments.

Keywords

Industry 4.0, horizontal integration, disruption management, rescheduling, performance improvements.

Introduction

Due to globalization, manufacturing companies are exposed to increasing competitive pressure. Therefore, companies are continuously developing a high level of customer orientation. While the focus in the past has been primarily on meeting customer expectations through impeccable products for reasonable costs, today customers expect flexibility and on-time deliveries. As delays in deliveries mean losses for customers, on-time deliveries are a significant success factor for manufacturing companies [1]. Both the technical complexity of today's products and the requirements for low-cost production lead to a specialization of production processes. A large proportion of industrially manufactured products are therefore produced in linked, multi-stage production processes which often involve several companies or production plants. The linking of production processes creates a material flow system. The material flow in and between the processes significantly determines the throughput times of the products within the system. Short lead times on the one hand are an indicator of high efficiency and flexibility of the value added system [2]. On the other hand, they ensure on-time delivery to the customer, since production plans, taking into account the throughput times, are often determined based on lead times.

To achieve low throughput times, a material flow without disruptions is required. Disruptions can cause downtimes in the material flow system. Downtimes increase throughput times and endanger on-time delivery. Therefore, disruptions pose a risk to the success of manufacturing companies. In this context it is problematic that production processes and material flow systems are often affected by disruptions [3]. The effects of occurring disruptions on target values such as lead times and thus on-time deliveries can be reduced by suitable reactive strategies. In multi-stage production processes, rescheduling is a frequently used reactive strategy [4]. The smaller the time delay between the beginning of a disruption and the reaction to it by rescheduling, the lower the downtime. The benefits of rescheduling are thus largely dependent on prompt communication between the actors involved. Empirical studies have shown, however, that organizational deficits such as missing interfaces and lack of communication often lead to long delays in the treatment of disruptions [5]. As a result, waiting times and delays in the execution of the rescheduling measure can occur. Then downtime cannot be avoided optimally, so possible performance improvements by rescheduling in the event of disruptions cannot be fully exploited.

State of the art

Disruption management

Disruption management in a manufacturing context is an established research area. According to Schumacher, a disruption in manufacturing environment exists if a process deviates from its planned procedure [6]. This includes e.g. a wrong estimation of processing times, job cancellations and machine breakdowns [7]. Through the process reference, a disruption is immediately different from a product fault which is characterized by a deviation of a physical feature that a product has to fulfil. Thus, errors are a result of manufacturing processes [8]. Heil defines that disruptions cannot be permanent, as permanent deviations in processes threaten the achievement of goals and thus the long-term existence of a company [9]. Disruptions are therefore described by a time course which means that disruptions have a defined start time and a defined end time after the occurrence of the cause.

For an efficient handling of disruptions, their effects must be known. Effects of disruptions are extended throughput times [10]. Extended throughput times can lead to longer delivery times which can endanger on-time delivery [11]. In multi-stage production processes, to control the production system it is reasonable to use KPIs that systematically assess the efficiency of the involved processes. Generally, throughput times indicate the efficiency of manufacturing processes [12]. Thus, the effects of disruptions on KPIs such as throughput times are particularly important. In most cases, disruptions in manufacturing environments can be considered economically relevant, so that ignoring them is an irrational behavior that results in monetary damage to the company. In order to limit these effects of disruptions, measures are required which are summarized in the term of 'disruption management'.

Disruption management includes all measures for the prevention, elimination and minimization of consequences of disruptions [13]. In principle, two different basic strategies can be distinguished. These are prevention strategies which are designed to avoid the occurrence of disruptions and reactive strategies that aim at reducing the effects of already existing disruptions [14]. In addition to the elimination of the disruption cause, such as the repair of tool or machine breakdowns, reactive strategies require adjustments of the production system to the disruption.

Rescheduling in the event of disruptions

Adjustments of the production system essentially include an intervention in ongoing production processes as well as the initiation of plan changes by production planning and control. Plan changes and replanning are called rescheduling [4]. First algorithm-based rescheduling approaches were developed, when the need for rescheduling in manufacturing environments was determined and computer-based control systems such as MRP-II entered production. Example, Brown refers to various reasons for rescheduling processes, such as changes in customer request dates, engineering changes or resource unavailability [15]. Therefore, a general heuristic framework for dynamic rescheduling processes is provided that enables replanning to be carried out efficiently.

Regarding rescheduling in case of disruptions, further research has been published in the area of operative production planning. By rescheduling, the initial schedule is adjusted in response to a disruption. For this purpose, several methods exist, such as right-shift rescheduling (RSR), total rescheduling and affected operations rescheduling (AOR) [7]. In RSR, the entire production process is delayed for the duration of the disruption, so the original schedule is shifted to the right on the time axis until the end of the disruption [16]. In general, RSR is the simplest and most intuitive way of rescheduling, but it increases throughput and lead times, so it is often used as comparison to methods which perform better [7]. Especially for total rescheduling and AOR, many different algorithms were developed to continuously improve the rescheduling performance. Total rescheduling essentially corresponds to full plan changes. It includes the entire procedure of the original schedule process, but only the remaining operations at the time of the disruption are taken into account [17]. Within total rescheduling, algorithms based on a binary activity tree were conceptualized to reschedule machines in the case of random disruptions [17, 18]. For this purpose, at first the examined system is broken down into local subsystems. For each subsystem, mathematical functions are built to search for local optima over time. Finally, in a new schedule, the optima are integrated iteratively and hierarchically until they are consistent with the schedules of the other subsystems. Cauvin, Ferrarini and Tranvouez extended rule-based algorithms by classifying rescheduling problems in multi-agent systems [19]. To this end, a general framework for improving decision-making in response to disruptions is provided. Based on the characterization of disruption types as well as suitable reaction possibilities, a cooperative solution strategy for the participating actors is developed. If only processes are rescheduled that are directly affected by disruptions, the rescheduling procedure is called affected operations rescheduling (AOR). A main goal of AOR consists in finding a schedule that has as little deviation from the original schedule as possible. For this purpose, weighted target functions are developed which contain e.g. the original completion time and the production times of already executed process steps [20]. In addition to these approaches in benefit-oriented optimization, costs that result from disruptions were integrated in algorithms and decision models [21, 22]. In total rescheduling and AOR, target functions are set up and optimized. However, with complex target functions and uncertainties, conventional algorithms in total rescheduling and AOR are stretched to their limits. Therefore, rescheduling procedures are increasingly developed with more extensive optimization techniques, e.g. genetic algorithms [23–25].

Horizontal integration of production processes

As shown in the introduction, there are several deficiencies in disruption management. They lead to delays in the treatment of disruptions, with negative impacts on the effect of rescheduling measures [9]. Studies which explicitly examine the effects of time delays between the occurrence of and reaction to disruptions on key performance indicators across multiple production plants do not exist. Cowling and Johansson summarize that existing scheduling procedures do not benefit from real-time information in general [4]. On the other side, e.g. Brynjolfsson and McAfee believe that by gaining information through increased data in the industry, business performance will be fundamentally improved [26]. This is because the speed with which decisions can be made will significantly increase by data-driven and technology-based management approaches, where decisions are made automatically.

In this context, a new approach in connection with Industry 4.0 is the horizontal integration via value added networks. Beyond IT-enabled integration, an essential aspect is the aggregation of information as well as the integration of processes across the entire supply chain using cyber-physical systems [27]. Cyber-physical systems are embedded, intelligent objects or processes that can independently and decentrally control each other through mutual digital networking. A main goal is to increase the efficiency of production processes and thus secure competitiveness in global comparison over the long term. Among other things, horizontal integration should be implemented through networked and intelligent production systems, digitization and real-time data exchange within the entire value creation network [28].

In general, horizontal integration is broadly conceived in the literature due to many possible applications in manufacturing and supply chains. Kieviet emphasizes the real-time availability and communication of information. Especially, this means that all the information needed about all parties involved in the production processes are available in real time [29]. This addresses one of the core problems and causes of inventory and waste within supply chains which is a lack of information across the supply chain. In terms of disruption management, Kaufmann and Forstner highlight opportunities to master complexity, increase efficiency and robustness, as well as timely responses to disruptions [30]. However, information-processing science does not precisely specify real-time information. Primarily the criticality of tasks characterizes real-time by definition [31]. The criticality is related to the deadlines of the tasks and possible system errors in exceeding the deadline. Hard real-time confirms that deadlines for tasks are not exceeded and thus a reaction to the task always takes place within the defined deadline. With soft real-time, statistical criteria guarantee the response to a certain extent. Therefore, soft real-time should be used primarily for tasks where no serious system failures are expected in the event of non-response [31]. In horizontally integrated production processes, the deadline for real-time needs to be defined in a way that negative effects on the system can be expected if rescheduling has not been operated within the deadline.

Performance improvements through real-time rescheduling

Scientific theories should be based on the application of a particular methodology to gain knowledge [32]. The central objective of our paper is to demonstrate the effects of disruptions on key performance indicators (KPI) and to measure the advantages of horizontal integration in the field of reactive disruption management. A quantitative research methodology is useful for measuring effects on KPI [12]. In quantitative research methodologies, data must be available. However, due to the complexity of disruptions and the application of reactive strategies in disruption management, it becomes clear that we cannot collect these data by empirical studies or experiments due to high cost effort. This is due to the fact that – in order to be able to measure the effects of horizontal integration and real-time communication – the same disruption with identical environmental parameters must occur at least twice or – depending on the scope of the analysis – several times with varied delay times in the reaction to the disruption.

In simulations, we can investigate the behavior of real systems by abstraction without this effort. It therefore is sensible to analyze our problem in a simulation model. Simulation models should represent real systems as simple as possible [33]. In our approach, the system design focusses on a multi-stage production process. For analyzing the benefits of real-time rescheduling in the event of disruption, a combination of two production plants is appropriate. Figure 1 shows our system in an abstract illustration.

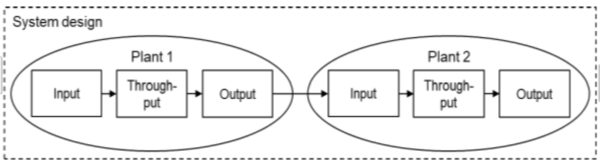

Fig. 1. System design.

Formal modelling of system design

We defined the average throughput time (t_t) of the objects which pass the system as our target value. An object is a unit of a manufactured product. The throughput time of an object is the timespan between the generation of an object in the input of Plant 1 until the object reaches the output of Plant 2. The absolutely expired simulation time is called t_{sim}.

In order to measure the effects of different rescheduling scenarios on throughput times, the simulated production system needs options to react in the event of a disruption. Therefore, in our model two different objects (Product A and Product B) are processed alternately according to a defined production plan. Each plant cannot produce both products at the same time, so the plants need to changeover between the products. The production parameters including process time per object (t_p), lot size per product (n_{lot}) and total amount of objects (n_{parts}) are the same for both products and in both plants. There are no set-up times or delivery times to reduce complexity. Plant 1 delivers the quantity of one lot size per product to Plant 2. The total number of objects is generated in the input of Plant 1 at the beginning of the simulation. There are no initial buffer stocks between both plants.

In the next step, we integrated the disruption and rescheduling behavior into the model design. At a defined point in time of the production process, a tool failure with a defined duration (t_{dod}) occurs in Plant 2 for one of the two products. This point in time is called beginning of disruption (t_{bod}). In consequence, Plant 2 reacts and changes over to the product without the tool failure for the timespan of the disruption. If then Plant 1 does not also change the product, downtimes may occur in Plant 2, because it receives objects of the product with the existing disruption, but no objects of the products it can process. The objects must then be processed after the disruption has been remedied which means an extension of their throughput times by the duration of the disruption. To achieve low throughput times, a simultaneous changeover in Plant 1 to the other product is necessary during the simulated disruption. With reaction in Plant 1, Plant 2 can then permanently manufacture the product without disruption despite the tool failure. In consequence, there are no more downtimes and thus no extension of throughput times.

Consequently, the relevant parameter in our approach for reaction is the delay between the occurrence of the disruption in Plant 2 and the executed rescheduling of the production plan in Plant 1 (t_{delay}). After the delay has elapsed, Plant 1 reacts. This point in time is called t_{inf}. After the end of disruption (t_{eod}), the system then changes to the initial plan again. Table 1 shows all parameters of our approach and introduces the abbreviations.

Table 1
Parameters of our simulation model.

Parameter	Description	Calculation
t_t	Average throughput time of all objects	$t_t = \sum_{i=1}^{n} \frac{t_{t,i}}{n_{\text{parts}}}$
$t_{t,i}$	Throughput time of object i	$t_i = t_{E,i} - t_{A,i}$
$t_{E,i}$	Point in time when object i exits the system	
$t_{A,i}$	Point in time when object i enters the system	
n_{parts}	Total amount of objects generated	
$t_{p,i}$	Process time of object i	
t_{dod}	Duration of disruption	
t_{bod}	Point in time of beginning of disruption	
t_{eod}	Point in time of end of disruption	$t_{\text{eod}} = t_{\text{bod}} + t_{\text{dod}}$
t_{delay}	Delay in the information about the disruption in Plant 2	
t_{inf}	Point in time of information in Plant 1 about the disruption in Plant 2 and reaction to it	$t_{\text{inf}} = t_{\text{bod}} + t_{\text{delay}}$
t_{sim}	Absolutely expired simulation time	

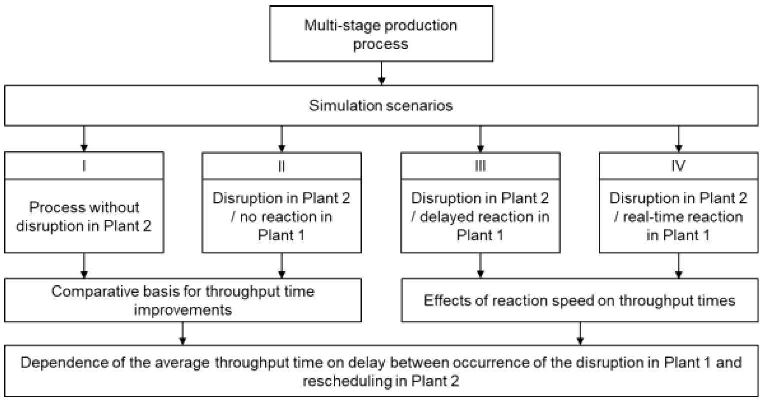

Fig. 2. Simulation scenarios.

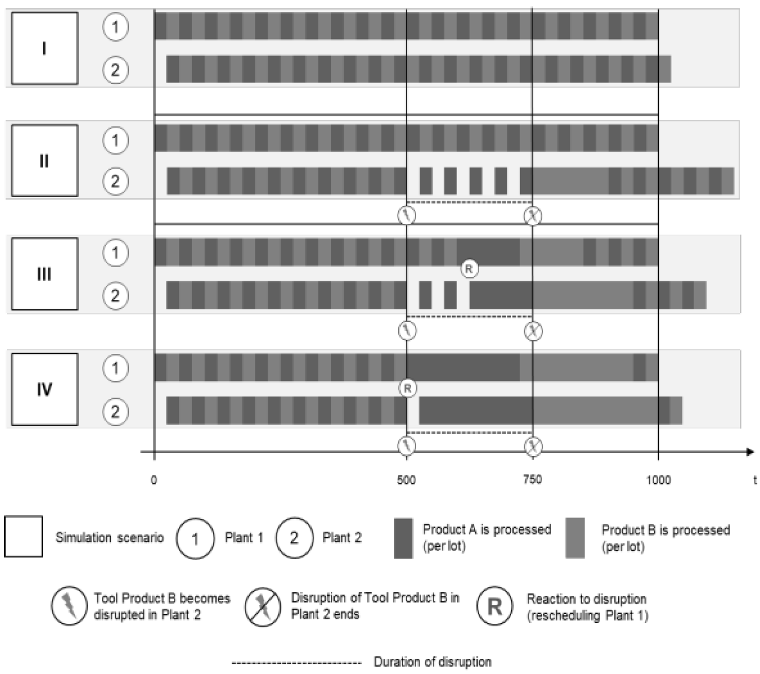

Fig. 3. Exemplary time course of the simulation scenarios.

In horizontally integrated networks, rescheduling can take place in real time ($t_{\text{delay}} = 0$), whereas without horizontal integration, rescheduling is delayed or generally does not take place. Based on these considerations, our approach includes four simulation scenarios represented in Fig. 2.

The simulation scenarios are illustrated in Fig. 3 for $n_{\text{parts}} = 1000$ objects, $n_{\text{lot}} = 25$ objects, $t_p = 1$ time unit (TU), $t_{\text{bod}} = 500$ TU and $t_{\text{dod}} = 250$ TU. Each box corresponds to the production of a lot size. The total length of the bars corresponds to the total processing time in the respective plant.

Implementation of the modelled system

After formally modelling the system and the behavioural logic, we implemented the model into a simulation tool. Tecnomatix Plant Simulation is a tool for discrete-event simulation. For modelling of material flow systems, the software provides predefined elements that can be connected by edges in a graphical modelling surface to create precedence graphs. Within the simulation, movable units (MU) can pass the modelled system via the edges. In our model, the two products A and B thus represent MU. The MU are generated in the source of the system and absorbed in the drain. Figure 4 shows a screenshot of the implemented model in the program interface of Tecnomatix Plant Simulation. The following overview explains the functions of each element connected by the edges.

Source

At the beginning of the simulation (t_{sos}), $n_{\text{parts}}/2$ quantity units (QU) for each of the two products A and B are generated in the source. These are passed on to the element Controller_1 alternating per lot sizes (n_{lot}). n_{lot} is set in Table_generate.

Controller_1

In order to map the behavioral logic of the rescheduling strategy, Plant 1 is modelled by two converging edges that lead into the respective tool of the product. Accordingly, the product is assigned via the correct edge to the corresponding tool of the product.

Buffer_A1_1 and Buffer_B1_1

The tools are modelled as a single station and therefore can only accommodate a maximum of one MU. The connection between the controller which immediately distributes the parts as batch sizes and the tool must therefore be buffered.

Tool_A1 and Tool_B1

These two elements correspond to the tools for the two products A and B in Plant 1. The products are processed in these elements. The process time for each product is one time unit (TU).

Buffer_A1_2 and Buffer B1_2

Our model design requires that only complete lot sizes can be delivered. Buffer_A1_2 and Buffer B1_2 collect MU of each product until a whole lot is reached. This is then passed to Controller_2.

Controller_2

Controller_2 controls the setup process for Plant 2 in the same way as Plant 1.

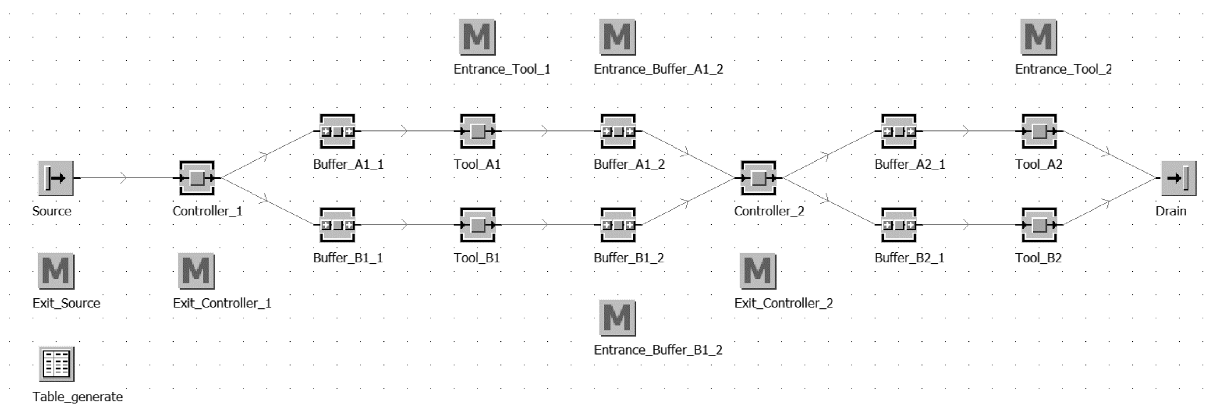

Fig. 4. Implemented model in Tecnomatix Plant Simulation.

Buffer_A2_1 and Buffer_B2_1

The considerations for Buffer_A1_1 and Buffer_B1_1 in Plant 1 apply analogously to Plant 2 for these two buffers.

Tool_A2 and Tool_B2

These two elements correspond to the tools for the two products A and B in Plant 2. Tool_A2 and Tool_B2 process the products analogously to Tool_A1 and Tool_B1. In contrast to Plant 1, no buffer is required after the tools, because the transfer after processing in Plant 2 is not relevant to the throughput times due to the boundaries of our system. Accordingly, a MU is immediately passed to the drain after processing.

Drain

The MU that passed the system are absorbed in the drain. Once the set n_{parts} has been absorbed, a simulation run is completed.

Implementation of model behavior

The simulation model is not yet executable, because we did not implement the model behaviour. Therefore, the object-oriented programming language SimTalk is included in Tecnomatix Plant Simulation. SimTalk is a scripting language to execute commands [5]. The commands allow the necessary flow of information. They are based on functions, operators, queries, data types, and variables. The syntax is based on the programming language Visual Basic. In Tecnomatix Plant Simulation, methods contain the commands which can be assigned to the elements of the model as input or output control. Accordingly, the commands are executed as soon as a MU enters or leaves the element. In the following, we explain the methods included in our model.

Exit_Source

This method forwards the generated BEs of the source to Controller_1.

Exit_Controller_1

Through this method, the MU are passed on to the correct tool in Plant 1.

Entrance_Tool_1

This method controls the setup process for both tools in Plant 1 by alternately opening and closing the outputs of the upstream buffers of the tools after a lot has been manufactured. In addition, the behaviour of Plant 1 with respect to the disruption in Plant 2 is controlled.

Entrance_Buffer_A1_2 and Entrance_Buffer_B1_2

The input control of the two buffers ensures that only whole lots can be passed on to Controller_2. For this, the outputs of the buffers are only opened when there is a whole lot within the buffer.

Exit_Controller_2

This method assigns the lot sizes of the MU to the correct tool.

Entrance_Tool_2

In this method, the setup process between both tools in Plant 2 is initially controlled. Furthermore, the method controls the starting time and end point of the disruption.

With the methods described, the implemented simulation model is basically executable. We verified and validated the model behaviour in multiple loops according to VDI 3633 [29]. For performing our experiments, still fixed system parameters and variable factors needed to be defined.

Factorial experiment design

The throughput time as the target value depends essentially on the processing times in the individual processes. The processing times are determined by the product of n_{parts} and t_p. We set these parameters in our experiments with $n_{\text{parts}} = 1000$ QU and $t_p = 1$ TU. In order to ensure a comparability of all rescheduling scenarios, we set t_{bod} at 500 TU after simulation start.

The goal of our simulation is to examine the effects on throughput times for different combinations of t_{dod} and t_{delay}. t_{dod} and t_{delay} were therefore varied. Likewise, the ability to react in our model design depends on n_{lot}, so this factor has been varied, too. Due to $t_{\text{bod}} = 500$ TU, rescheduling effects are possible in our system for t_{dod} up to 500 TU, because the simulation regularly ends after 1000 TU. For causing relevant effects, t_{dod} must have also a minimum duration, which is 100 TU. n_{lot} must not be too large for a number of 500 QU to be produced per product so that measurable effects of the disruption as well as the real-time reaction develop in the model. n_{lot} is therefore varied from 5 to 50 QU.

The system behavior should be represented by the average throughput time (t_t) in functional dependence of t_{delay}. The increment of t_{delay} ($n_{l,\text{delay}}$) is therefore in levels of processing times for multiple lot sizes as shown in Eq. (1), since the system can only react after finishing a lot size and as long as t_{delay} is smaller than t_{dod}

$$n_{l,\text{delay}} = \frac{t_{\text{dod}}}{n_{\text{lot}} * t_p}, \tag{1}$$

$n_{l,\text{delay}}$ – increments of t_{delay}, t_{dod} – duration of disruption, t_p – processing time, n_{lot} – lot size.

As an example, for the setting $t_{\text{dod}} = 100$ and $n_{\text{lot}} = 50$ the calculation results in three levels for t_{delay} (0, 50, 100) and for the setting $t_{\text{dod}} = 500$ and $n_{\text{lot}} = 25$ it results in 21 levels for t_{delay} (0, 25, 50, ..., 500).

n_{lot} and t_{dod} are varied in three steps. With the nine combinations of n_{lot} and t_{dod} and the calculation of the increment of t_{delay}, in total this results in 230 combinations and simulation runs for our factorial design. Table 2 shows the levels of all varied factors.

Table 2
Levels of all varied factors.

Factor	Levels
t_{dod}	100, 250, 500 TU
n_{lot}	5, 25, 50 QU
t_{delay}	$n_{\text{lot}} * 1$ for $i = 0$ to $i = n_{l,\text{delay}}$ with $i \in$ N0

In performing the simulations, we gradually varied the three factors according to our factorial design. The average throughput time (t_t) for each simulation run was transferred to an Excel spreadsheet.

Results

Preparation of the generated data

Regardless of whether there is a disruption or not, the total simulation run time essentially depends on the settings of n_{parts}, t_p and n_{lot}. According to the model design, the elapsed run time of an ideal simulation run is equal to the sum of the throughput times of the first and the last object processed without a disruption in the whole process, because then all objects have passed both plants steadily. In order to display the results independently of these system parameters, the generated simulation data first must be prepared. It is therefore appropriate to relativize the average throughput time through the references of an ideal simulation run. We defined the throughput factor (TPF) as shown in Eq. (2)

$$\text{TPF} = \frac{t_t}{t_{t,1} + t_{t,n}} \tag{2}$$

TPF – throughput factor, t_t – average throughput time, $t_{t,1}$ – throughput time of the first object, $t_{t,n}$ – throughput time of the last object.

For each simulation without disruption, TPF has an ideal value of 0.5. This value is used as a reference for the disruption effect as well as the improvements by rescheduling. Since the two products are linked in two processes with a processing time of one time unit, a TPF of 0.5 corresponds to a throughput of one object per time unit for the entire system.

Due to system design, t_{delay} must not exceed the duration of the disruption, in order to cause measurable effects in system behavior. To ensure comparability for all simulations performed, we relativized t_{delay} by t_{dod}. The relative information delay (RID) represents the relative delay of the information divided to the duration of the disruption shown in Eq. (3)

$$\text{RID} = \frac{t_{\text{delay}}}{t_{\text{dod}}}, \tag{3}$$

RID – relative information delay, t_{delay} – time of delay in the information on the occurred disruption, t_{dod} – downtime by disruption.

The relative information delay can take values between 0 and 1. An RID of 0 corresponds to a real-time reaction, whereas an RID of 1 means no reaction to the disruption.

Presentation and interpretation of the system behavior

To represent TPF as a function of the RID, we generated a scatterplot containing the prepared data of the 230 simulation runs. Figure 5 shows the generated TPF/RID diagram. For better clarity, lines connect the discrete points. Actual changes in the system behavior thus only result at the vertices of the lines. Each line corresponds to a specific combination of the levels of n_{lot} and t_{dod}. Consequently, three levels per factor lead to nine lines in total.

From the illustrated TPF/RID-diagram, one can derive various insights regarding the system behavior:

- The comparison between the value of TPF at RID 0 = and the value of TPF at RID = 1 of a curve represents the relative improvement by real-time rescheduling compared to no rescheduling.
- The larger t_{dod}, the greater TPF and thus the average throughput time, since the absolute simulation time increases with increasing duration of the disruption.
- The smaller n_{lot}, the smaller TPF and thus the average throughput time, since small lot sizes promote low throughput times and a faster reaction to a disruption.

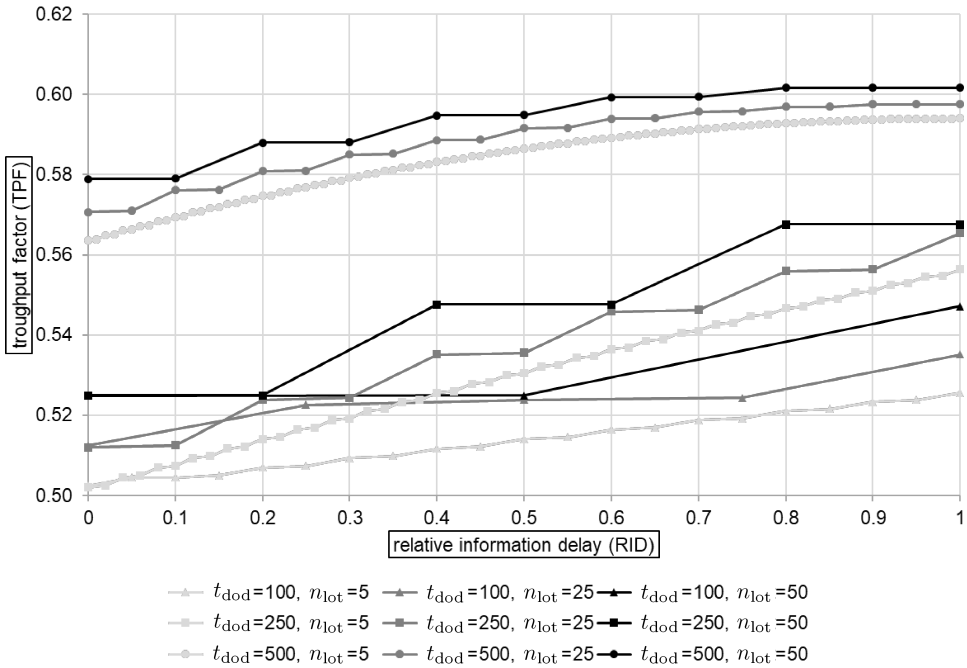

Fig. 5. TPF/RID-diagram.

- In particular, on the curves at $t_{dod} = 500$, it can be seen that the curves are not linear, but declining. The slope of the curves decreases which means that the benefit of the speed of information is reduced per level of t_{delay}. The marginal benefit of real-time information is the highest, since the system can benefit from the reaction the longest.
- n_{lot} and t_{dod} interact with each other to a small extent, since the curves for different levels of one factor shift approximately linearly vertically with the same setting for the other factor.
- With real-time communication (RID = 0), especially for small lot sizes and small disruption durations, improvements of TPF are achieved which can approximately reach the level of the process without a disruption (TPF = 0.5).
- Thus, in certain combinations of factors, the system is capable of almost completely absorbing the disruption effect on average throughput times through real-time rescheduling.

From the presentation and interpretation of the system behavior, the effects of the individual factors as well as the interactions between the factors cannot be analyzed exactly. For this reason, we additionally evaluated the simulation results using the Design of Experiments methodology (DoE).

Evaluation according to DoE methodology

For the evaluation of the simulation results, the lowest and highest factor settings are used in accordance with the generally accepted procedure of DoE methodology. This results in the factor variations and values of TPF shown in Table 3.

Table 3
Evaluation according to DoE methodology.

No.	RID	t_{dod}	n_{lot}	TPF
1	0	100 TU	5 QU	0.5024
2	1	100 TU	5 QU	0.5256
3	0	500 TU	5 QU	0.5636
4	1	500 TU	5 QU	0.5940
5	0	100 TU	50 QU	0.5249
6	1	100 TU	50 QU	0.5472
7	0	500 TU	50 QU	0.5789
8	1	500 TU	50 QU	0.6016

TU – Time Units, QU – Quantity Units.

We used the evaluation table to calculate the effects and interactions of the varied factors regarding to TPF. These are shown in Fig. 6. We see that each factor has an average effect on the value of TPF, but interactions between two or three factors cause a maximum change of 0.005 and thus can be almost neglected. The finding that real-time communication (RID = 0), especially for small n_{lot} and t_{dod}, results in improvements of TPF, which can reach almost the level of the process without a disruption (TPF = 0.5), results from the sum of the two individual effects and only to a small extent from an interaction between these two factors.

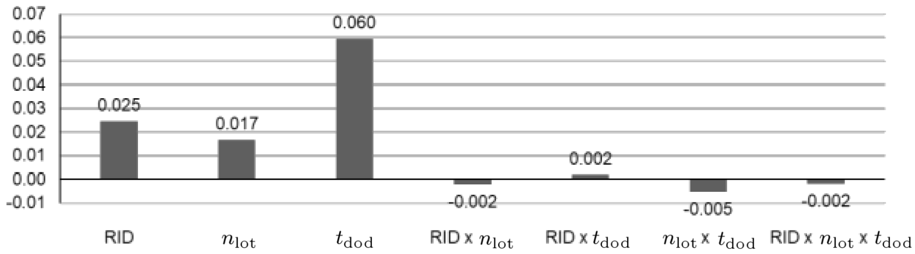

Fig. 6. Effect and interaction diagram of the varied factors.

With regard to the effects of the individual factors, it becomes clear that t_{dod} has the greatest effect on TPF. This was also evident in Fig. 2 by the vertical shift of the curves for equal n_{lot}, but different t_{dod}. However, the influence of t_{dod} is comparatively high, since the observation period was limited by the model design. The system's relatively high disruption time referred to the absolute simulation time result in a relatively high change in the average throughput time.

Furthermore, figure shows that real-time rescheduling has a larger average effect on disruption times than a small batch size (0.025 versus 0.017).

This can be seen, for example, in the comparison of line 2 (TPF = 0.5256) and line 5 (TPF = 0.5249) in Table 3. For the same value of t_{dod}, the value of TPF with real-time based rescheduling (RID = 0) and high n_{lot} is better than the value of TPF without real-time based Rescheduling (RID = 1) and low n_{lot}.

To determine the actual improvement of the averaged throughput time by real-time rescheduling, the percentage improvement in throughput factor must be calculated for a change between RID = 0 and RID = 1, as well as the same setting for the other factors. For each combination of n_{lot} and t_{dod}, we are able to calculate the ability of the system to absorb the disruption effect in terms of throughput time by comparing the relative improvement through real-time rescheduling. The calculation is based on the value of TPF with RID = 1 (TPF without rescheduling, hereinafter referred to as $\mathrm{TPF_{W/OR}}$), the value of TPF at RID = 0 (TPF with real-time rescheduling, hereinafter referred to as $\mathrm{TPF_R}$) and the ideal value of TPF (TPF = 0.5). Equation (4) shows the calculation of the disruption effect absorption

$$C_A = \frac{\mathrm{TPF_{W/OR}} - \mathrm{TPF_R}}{\mathrm{TPF_{W/OR}} - 0.5}, \tag{4}$$

C_A – absorption of disruption effects by real-time rescheduling, $\mathrm{TPF_{W/OR}}$ – TPF with RID = 1, $\mathrm{TPF_R}$ – TPF with RID = 0.

The absorption of the disruption effects by shifting between RID = 0 and RID = 1 are shown for the different factor combinations of n_{lot} and t_{dod} in Table 4.

Table 4
Absorption of disruption effects.

Lines in Table 3	$\mathrm{TPF_R}$ (RID = 0)	$\mathrm{TPF_{W/OR}}$ (RID = 1)	C_A [%]
1 and 2: n_{lot} = 5 QU, t_{dod} = 100 TU	0.5024	0.5256	90.63
3 and 4: n_{lot} = 5 QU, t_{dod} = 500 TU	0.5636	0.5940	32.34
5 and 6: n_{lot} = 50 QU, t_{dod} = 100 TU	0.5249	0.5472	47.24
7 and 8: n_{lot} = 50 QU, t_{dod} = 500 TU	0.5789	0.6016	22.34
Average			48.14

Overall, an average absorption of 48.14 % of the disruption effects results from real-time rescheduling in our factorial experiment design.

Discussion

We showed that real-time rescheduling strategies improve the performance of multi-staged production processes in the event of disruptions. The improvements are obtained by an absorption of the disruption effect regarding the average throughput time through a cooperative real-time rescheduling of the initial production plans. Instead of downtime because of a disruption, another product is manufactured in both involved processes.

In particular, for small n_{lot} and t_{dod}, we achieved an overall effect by real-time rescheduling which enables the system to nearly approach the performance level of the system without a disruption. The influence of the varied factors on the overall effect was evaluated by applying the DoE methodology. We found out, that the factor variation causes largely independent effects. Interactions between the system parameters only cause a small part of the total effect.

Since we found no significant interactions between the varied factors, a fundamental improvement can be assumed by real-time rescheduling in case of disruptions in multi-stage production processes. Occurring disruptions have a high relevance in real production processes, since a multiplicity of possible disruption causes exists and the occurrence can therefore often not be avoided preventively. Empirical studies have found that negative effects of disruptions are mainly caused by delays in dealing with the occurrence due to organizational issues such as lack of communication or complex information flows. With horizontal integration of value-added systems and the associated real-time availability of information on disruptions, real efficiency improvements emerge in multi-stage production processes. Competitive advantages may be possible, since the effects of disruptions on the material flow system decrease to such an extent that, for example, there are no delays in delivery dates.

With the assumptions and simplifications made in our model, there is also a need for further research on the evaluation of realizable efficiency improvements. In our methodology, only a two-stage, two-product production process was simulated to fundamentally examine the effects of real-time based rescheduling on key performance indicators in multi-stage production processes. However, real value-added systems often consist of a large number of processes which are also linked in a convergent or divergent manner to material flow systems. Disruption effects can then be weakened or increase for the successor processes and thus for the overall system. In addition, we did not take into account possible costs. In real production systems, rescheduling usually requires activities that can incur additional costs. In this context, we also assumed in our model that both products basically generate the same costs and the same income and thus achieve the same contribution. Accordingly, there was no prioritization between the products and delays for both products were considered equally problematic.

In horizontal integration of production plants, it would also be conceivable that a plant benefiting from the positive effects of rescheduling would provide incentives to the plant that reschedules. For example, these could be automated compensation payments. However, this requires innovative, activity-based costing models.

Moreover, the technical implementation of horizontal integration in terms of automated incentive systems and compensation payments is largely unexplored. Smart contracts based on crypto-currencies, which are integrated into IT systems, may possibly be used. Decentralized payment systems such as Ethereum or IOTA are available for this purpose. In further research, specific application concepts in production management should be examined in this context.

Declaration of interests statement

We have no conflicts of interest to disclose.

Data availability statement

The data that support the findings of this study are openly available in Mendeley Data at http://dx.doi.org/10.17632/8g4jbtp4pj.1

References

[1] Schuh G. et al., *(Monetary Value of in Time Deliveries): Decentralized, Market-Driven Coordination Mechanism Based on the Monetary Value of in Time Deliveries*, [in:] Proceedings of Global Business Research Conference, Kathmandu, pp. 1–13, 2013.

[2] Christopher M., *The Agile Supply Chain*, Industrial Marketing Management, 29(1), 37–44, 2000, doi: 10.1016/S0019-8501(99)00110-8.

[3] Wagner J., Burggräf P., Dannapfel M., Fölling C., *Assembly Disruptions – Empirical Evidence in the Manufacturing Industry of Germany, Austria and Switzerland*, International Refereed Journal of Engineering and Science, 6(3), 15–25, 2017.

[4] Cowling P., Johansson M., *Using real time information for effective dynamic scheduling*, European Journal of Operational Research, 139(2), 230–244, 2002, https://doi.org/10.1016/S0377-2217(01)00355-1.

[5] Cauvin A.C.A., Ferrarini A.F.A., Tranvouez E T.E., *Disruption management in distributed enterprises: A multi-agent modelling and simulation of cooperative recovery behaviours*, International Journal of Production Economics, 122(1), 429–439, 2009, https://doi.org/10.1016/j.ijpe.2009.06.014.

[6] Schumacher J., *Effizientes Störungsmanagement in der Produktion*, ZWF Zeitschrift Für Wirtschaftlichen Fabrikbetrieb, 104(3), 206–209, 2009, https://doi.org/10.3139/104.110037.

[7] Sundstrom N., Lennartson B., *Rescheduling affected operations – a purely predictive approach*, 13th International Workshop on Discrete Event Systems (WODES), pp. 71–78, 2016, https://doi.org/10.1109/WODES.2016.7497828.

[8] Lehmann F., *Störungsmanagement in der Einzel- und Kleinserienmontage: Ein Beitrag zur EDV-gestützten Montagesteuerung*, Aachen: Shaker Verlag, 1992.

[9] Heil M., *Entstörung betrieblicher Abläufe*, Wiesbaden: Deutscher Universitäts-Verlag, 1995.

[10] Kampker A., Wagner J., Burggräf P., Bäumers Y., *Criticality-focused, pre-emptive disruption management in low-volume assembly*, Paper presented at the 23rd International Conference on Production Research – Operational Excellence towards sustainable development goals (SDG) trough Industry 4.0, Manila, August 2–5, 2015.

[11] Burggräf P., Wagner J., Lück K., Adlon T., *Cost-benefit analysis for disruption prevention in low-volume assembly*, Production Engineering, 11(3), 331–342, 2017, https://doi.org/10.1007/s11740-017-0735-6.

[12] Jonsson P., Lesshammar M., *Evaluation and improvement of manufacturing performance measurement systems – the role of OEE*, International Journal of Operations & Production Management, 19(1), 55–78, 1999, doi: 10.1108/01443579910244223.

[13] Eversheim W., *Störungsmanagement in der Montage*, Düsseldorf: VDI-Verlag, 1992.

[14] Schwartz F., *Störungsmanagement in Produktionssystemen*, Aachen: Shaker Verlag, 2003.

[15] Brown M.C., *The dynamic rescheduler: conquering the changing production environment*, In Proceedings. The Fourth Conference on Artificial Intelligence Applications, pp. 175–180, 1988, https://doi.org/10.1109/CAIA.1988.196100.

[16] Wu S.D., Storer R.H., Chang P.-C., *A rescheduling procedure for manufacturing systems under random disruptions*, In New Directions for Operations Research in Manufacturing, Berlin, Heidelberg: Springer, 1992.

[17] Abumaizar R.J., Svestka J.A., *Rescheduling job shops under random disruptions*, International Journal of Production Research, 35(7), 2065–2082, 1997, https://doi.org/10.1080/002075497195074.

[18] Akturk M.S., Gorgulu E., *Match-up scheduling under a machine breakdown*, European Journal of Operational Research, 112(1), 81–97, 1999, https://doi.org/10.1016/S0377-2217(97)00396-2.

[19] Cauvin A.C.A., Ferrarini A.F.A., Tranvouez E.T.E., *Disruption management in distributed enterprises: a multi-agent modelling and simulation of cooperative recovery behaviours*, International Journal of Production Economics, 122(1), 429–439, 2009, https://doi.org/10.1016/j.ijpe.2009.06.014.

[20] Tang L., Zhang Y., *Parallel machine scheduling under the disruption of machine breakdown*, Industrial and Engineering Chemistry Research, 48(14), 6660–6667, 2009, https://doi.org/10.1021/ie801868f.

[21] Qi X., Bard J.F., Yu G., *Disruption management for machine scheduling: The case of SPT schedules*, International Journal of Production Economics, 103(1), 166–184, 2006, https://doi.org/10.1016/j.ijpe.2005.05.021.

[22] Xu X., Shang J., Wang H., Chiang W.C., *Optimal production and inventory decisions under demand and production disruptions*, International Journal of Production Research, 54(1), 287–301, 2015, https://doi.org/10.1080/00207543.2015.1073402.

[23] Man K.F., Tang K.S., Kwong S., Ip W.H., *Genetic algorithm to production planning and scheduling problems for manufacturing systems*, Production Planning & Control, 11(5), 443–458, 2000, doi: 10.1080/09537280050051942.

[24] Mattfeld D.C., Bierwirth C., *An efficient genetic algorithm for job shop scheduling with tardiness objectives*, European Journal of Operational Research, 155(3), 616–630, 2004, doi: 10.1016/S0377-2217(03)00016-X.

[25] Tay J.C., Ho N.B., *Evolving dispatching rules using genetic programming for solving multi-objective flexible job-shop problems*, Computers & Industrial Engineering, 54(3), 453–473, 2008.

[26] Brynjolfsson E., McAfee A., *Big Data: The Management Revolution*, Harvard Business Review, 90(10), 60–68, 2012.

[27] Yu W., *The effect of IT-enabled supply chain integration on performance*, Production Planning & Control, 26(12), 945–957, 2015, https://doi.org/10.1080/09537287.2014.1002021.

[28] Acatech, Umsetzungsempfehlungen für das Zukunftsprojekt Industrie 4.0: Abschlussbericht des Arbeitskreises Industrie 4.0. Frankfurt am Main, 2013.

[29] Kieviet A., *Digitalisierung der Wertschöpfung: Auswirkung auf das Lean Management*, [in:] Erfolgsfaktor Lean Management 2.0, Künzel H. [Ed.], pp. 41–59, 2016, Berlin, Heidelberg: Springer, https://doi.org/10.1007/978-3-662-49752-4_3.

[30] Kaufmann T., Forstner L., *Die horizontale Integration der Wertschöpfungskette in der Halbleiterindustrie – Chancen und Herausforderungen*, [in:] Industrie 4.0 in Produktion, Automatisierung und Logistik, Bauernhansel T., ten Hompel M., Vogel-Heuser B. [Eds], pp. 359–367, 2014, Wiesbaden: Springer Fachmedien Wiesbaden, https://doi.org/10.1007/978-3-658-04682-8_18.

[31] Sprunt B., Sha L., Lehoczky J., *Aperiodic task scheduling for Hard-Real-Time systems*, Real-Time Systems, 1(1), 27–60, 1989, https://doi.org/10.1007/BF02341920.

[32] Aken J.E. van, *Management Research Based on the Paradigm of the Design Sciences: The Quest for Field-Tested and Grounded Technological Rules*, Journal of Management Studies, 41(2), 219–246, 2004, https://doi.org/10.1111/j.1467-6486.2004.00430.x.

[33] VDI 3633-1:2014-12.2014, *Simulation of systems in materials handling, logistics and production – Part 1: Fundamentals*, Berlin: Beuth Verlag.