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MANAGEMENT OF DISRUPTIONS IN PRODUCTION SYSTEMS USING SIMULATION

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Dedicated to Prof. Toshi Ibaraki on the occasion of his 65th birthday.

Abstract: Recently, research in various areas of operations management and scheduling has begun to focus on online optimization and rescheduling in cases where disturbances or changes of the data occur. Especially disruptions may have a considerable impact on the performance of production systems. In this paper a simulation model is proposed and applied to a hybrid flow shop system for the purpose of evaluating different strategies for managing disruptions. The investigated strategies aim both at the shop floor itself and the planning and control of the shop floor. For assessing different strategies for managing disruptions, job oriented and capacity oriented performance measures as well as so-called instability measures are applied. These instability measures enable estimating unfavorable consequences from changing existing schedules based on disruptions.

Key words: *production models, hybrid flow shop, simulation, reactive scheduling, rescheduling*

Mathematics Subject Classification: *90B30, 68U20, 90C27*

1 Introduction

Various studies of real production systems (see, e.g., [13, 21, 30]) point out that disruptions affecting the production as well as its planning and control may occur quite frequently. Thereby, existing schedules as well as further planning activities – based upon these schedules – may become obsolete. This causes planning nervousness, also called planning instability [17, 23, 39]. To overcome the negative impact of disruptions, two different strategies may be distinguished: reactive strategies and preventive strategies [5]. Reactive strategies are applied after the occurrence of a disruption and aim at the reduction of negative consequences of disruptions. Contrary to this, preventive strategies try to eliminate the cause of disruptions beforehand.

In this paper we present a simulation model that provides an opportunity for assessing several reactive and preventive strategies for managing disruptions regarding their effects on the production system *and* its planning and control. A special feature of the simulation model is the treatment of a dynamic scheduling problem as a series of static problems, which are solved in a rolling horizon manner. That is, both creating a schedule as well as its subsequent updating are modeled. This allows to investigate a number of strategies for managing disruptions. Respective criteria are the efficiency of capacity utilization and order processing, but also the extent of subsequent changes to existing schedules caused by disruptions.

The paper is organized as follows: Section 2 gives some references dealing with the management of disruptions in production systems. In the third section we present the main elements of the proposed simulation model. Section 4 describes the applied performance measures that enable the evaluation of different strategies for managing disruptions regarding the efficiency of capacity usage and job processing as well as the planning instability. In the fifth section we describe the simulated scenarios and analyze the sampled data. We conclude with a summary of some essential results.

2 Literature Review

In the sequel we provide a brief survey of some relevant references on disruptions in production systems. Our main focus is on providing a clarification of the corresponding planning and control and giving a few exemplary references without attempting to provide a comprehensive review. For a more comprehensive survey of robust scheduling and additional German references related to our work see [41] and [42].

One may distinguish

- approaches where no anticipatory schedule is generated (priority rule-based scheduling ([12, 36], for a dynamic rule selection see [43]), opportunistic scheduling [10], multi-agent systems [13, 44])
- procedures to revise schedules using ideas from the interface between operations research and artificial intelligence (*match-up-scheduling* [2, 3], *switching-approach* [29], *miscellaneous algorithms for rescheduling* [1, 15, 27, 51], *approaches based on local search* [53])
- robust and flexible scheduling approaches [7, 14, 16, 20, 25, 31, 35, 47, 52]
- suggestions of simulation and/or knowledge-based frameworks that assist production managers in rescheduling and handling disruptions [4, 26, 32, 45]
- conducting simulation experiments, e.g., the simulation of revising schedules over time. To some extent specialized methods in managing disruptions are also considered [1, 15, 22, 39, 40, 54]

In the vast majority of the mentioned publications specialized approaches for managing disruptions in production systems are considered. A comparison of various strategies for managing disruptions seems to be the exception, and in those few cases the assumptions are quite restrictive. Furthermore, the implemented performance measures do not seem to be appropriate to evaluate the production system and its planning and control under the impact of disruptions. The discrete-event simulation model proposed below aims at overcoming the mentioned shortcomings and permits the investigation of different strategies to manage disruptions.

3 A Simulation Model for the Management of Disruptions

The core of the simulation model is the treatment of a hybrid flow shop production system and its planning and control in the context of disruptions. In the presented simulation model the creation, implementation, the subsequent modification of schedules as well as rescheduling from scratch are emulated on a rolling horizon basis (see also [37, 42]). The revision of a schedule is required if one of the following simulated events occurs:

- a pre-determined planning period ends and a new schedule is required
- an order arrives
- a rush order arrives
- a machine breaks down

In the production system that we consider the latter two types of events (rush orders, machine breakdowns/failures) are the assumed disruptions. Inter-arrival times of orders as well as inter-arrival times of breakdowns for each machine were sampled from an exponential distribution.[1] Thereby, in terms of machine failures only those times are relevant where the machine is active (see also [24]).

In this paper we assume a special production system that arises in various settings related to extending ideas in flow shop, job shop, and resource constrained project scheduling (see, e.g., [6, 34]). The investigated production system is a hybrid flow shop system (see, e.g., [11, 19, 28, 38, 48] for some references). Instead of machines we consider machine stages, i.e., each machine is replaced by a number of parallel machines to build such a stage. As in a flow shop system each job has to be processed in the same order, first at stage one, then at stage two and so on. That is, different to a common flow shop system our hybrid flow shop system contains several identical parallel machines at each stage. Because of the existence of these identical parallel machines there is no distinction in processing times at a stage. Furthermore, we also consider sequence dependent setup times in the simulation model.

Fig. 1 depicts the flow of material in the investigated production system. It is a hybrid flow shop system with three production stages and five identical parallel machines at each stage. Concerning the range of products it is assumed that there are ten different products produced by the production system. The expected value of the stochastic inter-arrival times of orders is one day; i.e., on the average there are about 50 incoming orders per five days week.

In order to create a schedule for the production system, a local search procedure based on the Threshold Accepting (TA) algorithm [9] is applied. Due to the complexity of the considered scheduling problem (see, e.g., [11]), exact solution techniques had to be discarded. The solution of the scheduling problem is encoded by a solution vector. This vector represents the permutation or sequence π of n jobs that have to be assigned to machines. Every job of the vector π has to be processed at every stage. An actual schedule is generated by decoding the solution vector π as follows: We consider all jobs in π in order and look for each job at every stage for a machine that can finish the job as early as possible taking into account the incurred sequence dependent setup times. In doing so, the sequence dependent setup times are incorporated implicitly. As an exception, a slightly different approach of this step in decoding the solution vector is as follows: If there is a machine that causes, in combination with a lower setup time, a marginal delay in finishing a job in comparison to the machine with the minimum finishing time, this machine is selected. The maximum value of this marginal delay is determined by a parameter of the simulation model. Furthermore, ties are broken such that a machine with minimum setup time is chosen. However, if more than one solution exists, an additional parameter is taken into account: the elapsed time since the last usage of a machine. In this case a job is assigned to the machine with the minimum elapsed time since its last usage.

[1] The exponential distribution characterizes a constant rate of machine breakdowns. This applies, e.g., to electronic components, engines after an initial brake-in phase as well as breakdowns due to an exceeding of load limits of elements; see, e.g., [46].

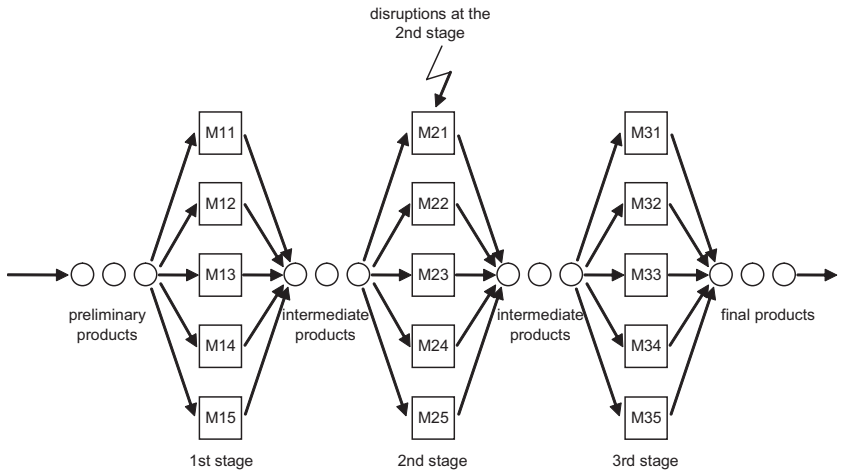

Figure 1: Flow of material in the investigated hybrid flow shop system

The following objectives are considered to be relevant with respect to the creation of a schedule in the simulation model:

- Minimizing the mean tardiness with respect to the earliest possible finishing times of jobs in the production system assumed as due dates
- Minimizing the sum of the sequence dependent setup times
- Minimizing the maximum completion time of a static schedule

The earliest possible finishing time of a job is determined by its release time and its processing times at the production stages, assuming that there are no sequence dependent setup times, breakdowns or delays in starting its execution.

The mentioned objectives are applied in lexicographical order. The main objective is the *minimization of the mean tardiness with respect to the earliest possible finishing times*; subordinate objectives are the *minimization of sequence dependent setup times* and the *minimization of the maximum completion time*. In a lexicographical order first the main objective is applied. If there are identical solutions with respect to the objective function value, then the subordinate objective is pursued and so on.

4 Performance Measures

As mentioned in the previous section, in the presented simulation model the creation, implementation, the subsequent modification of schedules as well as rescheduling from scratch are simulated in the context of a failure prone production system. Using the simulation model, several strategies for managing disruptions are examined. In order to evaluate the investigated strategies for managing disruptions, appropriate performance measures have to be specified.

Due to difficulties in quantifying different approaches for managing disruptions in terms of monetary measures [5], they are substituted by efficiency as well as instability measures.

4.1 Efficiency Measures

Generally, efficiency refers to the ratio between the input and the output of any system. In the conducted simulation studies the quantification of efficiency is operationalized by two different measures: a capacity oriented and an order oriented performance measure.

For an elapsed reference period a capacity oriented performance measure records how much of the capacity of the production system is used for setups (i.e., fraction of the resource time used for changeovers). The amount of setup times substantially depends on the sequence of scheduled jobs, thus it is an important measure for estimating the quality of the created schedules. Based on the setup times, a measure U^S within the interval [0,1] can be stated:

$$U^S = \frac{\sum_{o \in O} t_o^S}{\kappa} \tag{1}$$

where

t_o^S time used for setups in a reference period for operation o
O set of operations or changeover activities for operations which are processed within a reference period
κ available time (capacity) in a reference period

Order oriented performance measures consider temporal aspects regarding order processing. An often applied measure is the tardiness (see, e.g., [3, 7, 39]). The hybrid flow shop problem under consideration does not include given due dates. Therefore, we define artificial due dates for another performance measure, R. This measure records the mean tardiness with respect to the earliest possible finishing times of jobs in the production system assumed as due dates. As mentioned in Section 3, the earliest possible finishing time of a job is determined by its release time plus its processing times at the production stages. Considering the case that a job on a machine for one product type follows another job of the same product type on the same machine, a lower bound for the sequence dependent setup times is zero and will be assumed for all cases when these artificial due dates are defined. With this, R takes non-negative values and is defined as follows:

$$R = \frac{\sum_{j \in J} (C_j - (t_j^{RT} + \sum_{s \in S_j} t_{js}^{PT}))}{|J|} \tag{2}$$

where

C_j earliest possible completion time of job j
S_j set of production stages of job j
t_{js}^{PT} processing time of job j at production stage s
t_j^{RT} release time of job j
J set of jobs that are completed in a reference period

For a rolling horizon environment with rescheduling in equidistant time intervals note the following: If a job enters the production system between the construction of two new

schedules, even if it is going to be scheduled after its release time, this already contributes to the flow time of the job.

The computation of U^S and R refers to identical time buckets and is performed in equidistant time intervals, respectively.

4.2 Instability Measures

In scheduling, the mainly adopted instability measures quantify the changes in assignments of operations to machines (see, e.g., [1, 8, 16, 18, 50, 53]). For this purpose, the assignments for a certain time span in one schedule are compared with the assignments for the same time span in the previous schedule.

Measuring Schedule Changes: Measuring schedule changes requires the

- definition of the length and position of the comparison period of two schedules and the
- calculation which changes within a schedule shall be considered as relevant for measuring schedule changes.

There are different approaches available for comparing subsequently created schedules. The approach that is applied here is illustrated in Fig. 2 where the schedules are indicated by dotted lines. Fig. 2 also illustrates the planning horizon of the schedules as well as the length of the comparison periods.

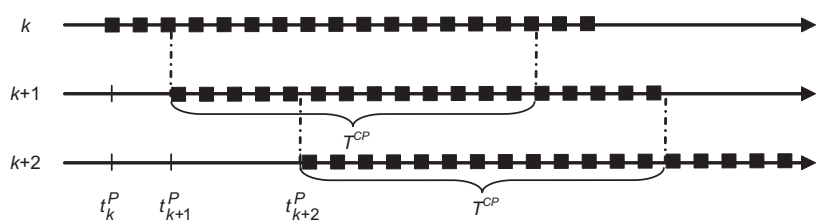

Figure 2: Length and position of comparison periods in schedules

The beginning of the particular schedules in Fig. 2 is at time t_k^P, t_{k+1}^P and t_{k+2}^P; the indices k, $k+1$ resp. $k+2$ denote individual plan generations. Based on the assumption that schedules are revised if stochastic events occur, the time span between the revision of schedules is varying. The length T^{CP} of the comparison periods is influenced by the question which schedule changes are considered to be relevant for measuring schedule changes. For the investigated production system the following changes concerning the operations in a schedule are assumed to be relevant for measuring the changes of a schedule:

- time shifts of operations
- switching the planned execution of an operation from one machine to another one
- removing an operation from a schedule
- adding an operation to a schedule

In the investigated rolling horizon environment removing an operation from a schedule means that an operation is removed temporarily. It is either postponed until the end of the comparison period or it is considered within the next planning period.

Changes in the schedules are handled differently, depending on the elapsed time from the point in time of creating the schedule. In this context it can be presumed that schedule changes in the near future are more relevant for applying the schedule respectively measuring schedule changes happening several days in the future.

Some types of changes are handled independently from the affected planning period. Regardless of the affected planning period, each elimination and each addition of an operation are interpreted as a relevant change of a schedule. In contrast to this, time shifts of operations as well as moves of operations from one machine to another one are handled differently. In the so-called *close-up-range* all time shifts of operations in a schedule are interpreted as a change of a schedule. In contrast, in the so-called *distant-range* only those time shifts of operations are considered to be relevant where the start time of an operation changes to another period (see Fig. 3). The beginning of a period could be, e.g., the beginning of a day or a shift.

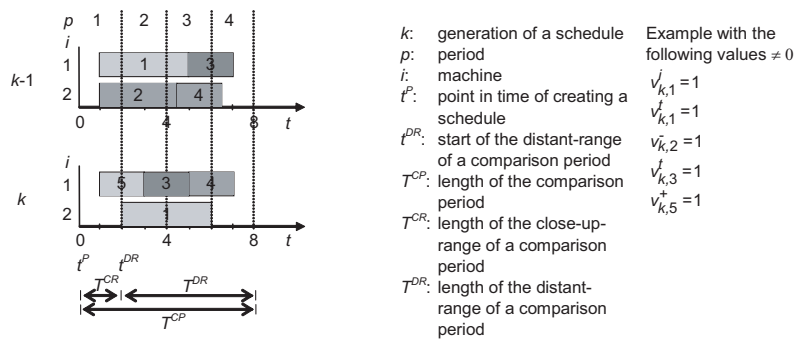

Figure 3: Example of two schedules created subsequently [2]

The changes concerning the devoted machines are also managed differently. For this type of changes it is assumed that they are only relevant when the affected operations start within the close-up-range of the comparison period.

The measure for quantifying changing of two subsequently created schedules $k-1$ and k with the operations $o \in O_{k-1}$ resp. $o \in O_k$ is called ν_k. It is calculated as follows:[3]

$$\nu_k = \sum_{o \in O_k \cap O_{k-1}} \left(1 - \left(1 - \nu^t_{ko}\right)\left(1 - \nu^i_{ko}\right)\right) + \sum_{o \in O_k} \nu^+_{ko} + \sum_{o \in O_{k-1}} \nu^-_{ko} \tag{3}$$

The values ν^t_{ko}, ν^i_{ko}, ν^+_{ko} and ν^-_{ko} indicate whether temporal (ν^t_{ko}) or machine oriented (ν^i_{ko}) changes occurred or if operations were removed (ν^-_{ko}) or added (ν^+_{ko}). For the example in Fig. 3 ν_k takes the value $\nu_k = 4$.

[2]The dotted vertical lines in the gantt charts distinguish different periods. Note that operation 4 changes the machine beyond the close-up-range and its start times in k and $k-1$ are both within the same period p. Therefore, values for indicating temporal or machine related changes regarding this operation are zero.

[3]For further approaches concerning the modeling of planning stability see, e.g., [49].

Definition of Instability Measures: The proposed instability measure represents a surrogate measure concerning the effort that results from subsequent revisions of existing schedules. For this purpose it is insufficient to evaluate the extent of changes ν_k of only two consecutive schedules. Instead of this it has to be taken into account that several revisions of schedules within a reference period may occur. This is provided by the non-negative integer measure

$$\eta = \sum_{k \in K} \nu_k \tag{4}$$

with K indicating the set of indices of plan generations within a reference period. It represents the grand total of schedule changes caused by multiple revisions of existing schedules within a reference period.

5 Simulated Strategies for Managing Disruptions

For a simulation of our production system and its planning and control, several investigations are possible. On one hand, various changes of the considered production system are simulated that represent different preventive strategies for directly affecting disruptions. On the other hand, changes of the production system are studied that represent different reactive strategies to manage schedule disruptions. The investigations are executed by means of two experimental designs [33], i.e., two factorial designs called I1 and I2. The factors in the experimental designs (F1 to F7) represent a set of varied parameters within the simulation model. For the statistical analysis of the simulation results an analysis of variance (ANOVA) as well as multiple comparisons according to Scheffé [33] have been conducted. In order to obtain reliable results, 35 replications are carried out for each setting in the experimental design. The length of one replication is fixed at 144 days running time of the production system. The warm-up period is fixed at 34 days[4], the comparison of two schedules covers a period of five days. The first day of this period constitutes the close-up-range of the comparison period, the remaining four days represent the distant-range of the comparison period.

5.1 Investigation of Preventive Strategies

Investigation I1 shall answer the questions how

- the mean time between failure
- the downtime of a machine
- the proportion of rush orders to the total number of orders
- the setup times after a machine failure

affect the performance measures U^S, R and η and whether the investigated production system could be ameliorated by applying preventive strategies for managing disruptions. The investigation is carried out using a rolling horizon. Rescheduling from scratch is executed regularly every five days, where new orders are also incorporated. A machine failure results in a time-shift of the affected operations, or, if an operation can be started earlier on another

[4]With respect to fixing the number and the length of replications within a simulation study as well as for predefining the initial phase of a replication see [24].

machine, it is moved to that machine. An incoming rush order triggers an immediate revision of an existing schedule. The operations of rush orders are scheduled as early as possible. If required, operations that are not operations of rush orders and that have not yet been started are shifted to the right in order to enable the insertion of the received rush orders into the schedule.

Tab. 1 provides the factors and factor levels of investigation I1. The average values of the considered performance measures are shown in Fig. 4*a*–4*c*.

The variance analysis reveals that all factors F1 to F4 significantly influence the performance measures U^S, R and η. In addition, there are interactions between F1 and F2 as well as F1 and F4 and, with respect to U^S and η , between F2 and F4. Due to the results of the multiple comparisons it can be deduced that all settings related to a factor are different.

Table 1: Factors and factor levels of investigation I1

Factor	Problem Parameter	Value	Factor Level
F1	Mean time β_{si}^B between failure	64 ($\hat{=}$ 2 days)	$\underline{1}$
	(exponential distribution) of all	128 ($\hat{=}$ 4 days)	2
	machines i at production stage s	256 ($\hat{=}$ 8 days)	3
F2	Expected value t_{si}^{DT} of the downtime	4 ($\hat{=}$ 2h)	$\underline{1}$
	(beta distribution) of all machines i	2 ($\hat{=}$ 1h)	2
	at production stage s	1 ($\hat{=}$ 30 min)	3
F3	Proportion R^{Prop} of rush orders of	0%	1
	the total number of incoming orders	10%	$\underline{2}$
		20%	3
F4	Setup times t_{0zsi}^S for product z after	4 ($\hat{=}$ 2h)	$\underline{1}$
	repair of a failed machine i at	2 ($\hat{=}$ 1h)	2
	production stage s	1 ($\hat{=}$ 30 min)	3

The graphs in Fig. 4*a*–4*c* point out that the variation of the mean time between failure (F1) affects the performance measures stronger than the variation of the expected values of the downtime of machines (F2). Along a decreasing number of failures (F1), the impact of varying both the expected downtime (F2) and setup times after the repair of a failed machine (F4) decreases, too. Changing the proportion of rush orders of the total number of incoming orders (F3) only affects the level of the performance measures. However, an alteration of the effects of other factors cannot be noticed.

In the following, one specific combination of factor levels represents a production system that is assumed to be given and that should be improved. The factor levels of this production system are F1-1, F2-1, F3-2 as well as F4-1.[5] The data obtained in the simulation studies are used to calculate the percentage deviation of the considered performance measures U^S, R and η by varying the factor levels of the examined factors. The measures to improve this production system are represented by the different levels of F1 to F4. Examples of specific actions may be: increasing the mean time between failure by an improved preventive maintenance (F1), shortening the downtime of a failed machine by exchanging assembly groups instead of repairing component parts on-site (F2), reducing the number of rush orders by altering the policy of accepting orders (F3) or reducing the setup times after the repair of a failed machine due to applying improved repair and setup techniques (F4).

[5]In Tab. 1 these factor levels are underlined, in Fig. 4*a*–4*c* they are marked with "×".

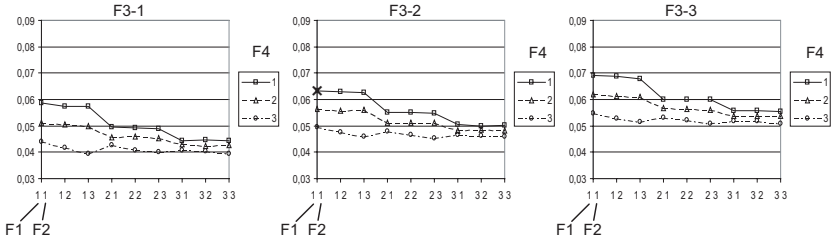

Figure 4*a*: Average proportion of setup times U^S of the total capacity

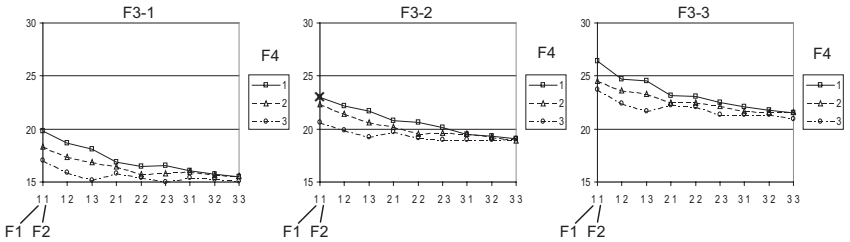

Figure 4*b*: R (mean tardiness)

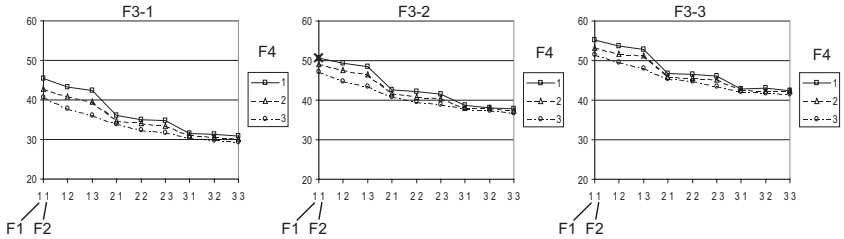

Figure 4*c*: Average values of the instability measure η

The resulting changes ΔU^S, ΔR and $\Delta\eta$ are visualized in the diagrams of Fig. 5 where positive values represent deteriorations and negative values represent ameliorations. SRI provides the mean over the changes of the three considered performance measures (Setup, R, Instability).

Fig. 5 points out that there are different factor levels and thus different actions to enhance the production system. Beyond this, it becomes clear that different actions to improve the production system may be substituted for each other and that an improvement with respect to one performance measure improves others. The similar effect of the analyzed preventive strategies with respect to different conditions as well as in reference to different performance measures becomes obvious according to the similarity of the four diagrams in Fig. 5. The homogeneous effect on the performance measures U^S, R and η also results in a similarly structured surface of the performance measure SRI. As a result of investigation I1, it has been demonstrated that the investigated preventive strategies for managing disruptions are adequate to improve the considered failure prone production system.

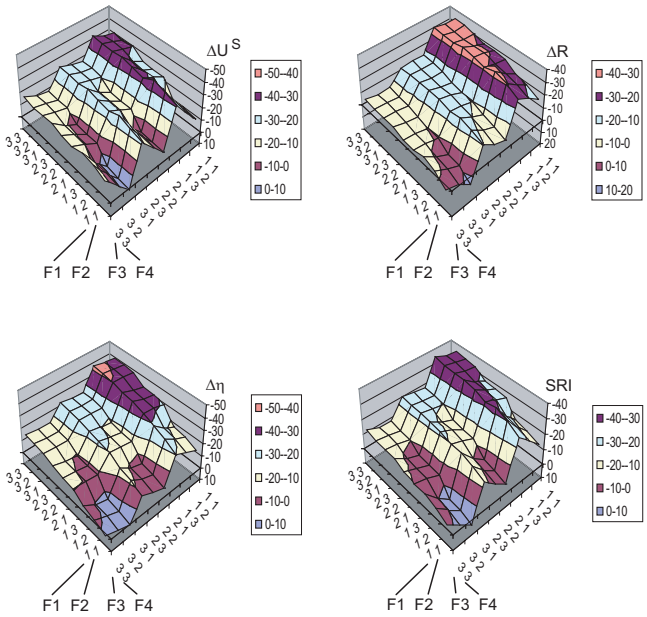

Figure 5: Percentage changes of the performance measures U^S, R and η as well as values of SRI

5.2 Investigation of Reactive Strategies

Investigation I2 shall answer questions regarding the effects of different strategies for scheduling in a production system that is exposed to disruptions. In this context it is investigated how

- different strategies for dispatching orders
- different strategies for reacting to machine failures and incoming rush orders

affect the performance measures U^S, R and η and in which way the investigated production system could be improved. Thereby, it is of particular interest how the performance measures are affected by different operational conditions. In the present investigation these operational conditions are represented by different characteristics of machine failures (many short, few longer and no breakdowns at all). In Tab. 2 the parameters varied in investigation I2 are reported.

In the following we explain the qualitative factors F5, F6 and F7 in more detail. Factor F5 applies both to the method of how to manage incoming orders and the time interval between rescheduling. Regarding the different types of managing incoming orders and time intervals between rescheduling, the following cases are distinguished: *Strategy SF* represents the typical case of a rolling horizon environment where non-rush orders are first added to a pool of orders. If the time for rescheduling is reached, the operations of these orders are considered in the new schedule besides other operations of orders that arrived in the meantime. In SF rescheduling occurs in constant and predetermined intervals. In contrast

[6] M represents a large number.

Table 2: Factors and factor levels of investigation I2[6]

Factor	Problem Parameter	Value	Factor Level
F1	Expected operation time of all machines i	64 ($\hat{=}$ 2 days)/	1
	at production stage s between failure /	4 ($\hat{=}$ 2h)/10%	
	downtime / proportion of rush orders	128 ($\hat{=}$ 4 days)/	2
	($\beta_{si}^{B}/t_{si}^{DT}/R^{Prop}$)	8 ($\hat{=}$ 4h)/5%	
		M/0/0%	3
F5	Strategy whether there is a rescheduling	SF/320 ($\hat{=}$ 10)	1
	from scratch in fixed intervals provided	SF/160 ($\hat{=}$ 5)	2
	(SF) or not (SV) / time interval between	SF/64 ($\hat{=}$ 2)	3
	rescheduling from scratch ([days])	SF/32 ($\hat{=}$ 1)	4
		SV	5
F6	Strategy for reacting to incoming rush	R1	1
	orders	R2	2
		R3	3
F7	Strategy for reacting to machine	B1	1
	failures	B2	2
		B3	3

to SF, in *strategy SV* rescheduling is not provided in equidistant intervals. Instead of that, after an order comes in its operations are assigned to machines immediately. If there are operations already assigned to machines, the orders are added to the existing schedule. Otherwise, if a machine is idle, subject to the production stage, the job on this machine may start immediately.

Regarding the reaction to an incoming rush order (F6), three strategies are considered in the simulation model. According to *strategy R1*, the operations of rush orders are inserted in an existing schedule immediately after their arrival and as early as possible. Thereby, if necessary, operations which are not operations of rush orders and which have not been started are shifted to the right in order to enable the insertion of operations of incoming rush orders into a schedule. Contrary to R1, in *strategy R2* shifting of operations is not provided. Instead the operations of a rush order are simply added to an existing schedule, so that the schedules only sustain marginal changes. In *strategy R3* rush orders are handled like the remaining orders.

Moreover, there are three strategies for dealing with machine failures (F7). In *strategy B1* particular operations that are directly or indirectly affected by machine failures are shifted to another machine and/or put forward in time. Note that only operations are shifted which have not yet been started. If necessary, consecutive operations on a machine have to be shifted, too. According to *strategy B2* all operations which are directly or indirectly affected by a machine failure and which have to be shifted are first removed from the schedule; subsequently they are appended to the schedule again. Thus, there are no changes regarding the remaining operations. Consequently, the level of planning instability may be low. In *strategy B3* the occurrence of a failure initiates a rescheduling from scratch. In doing so, operations that are not contained in the preceding schedule as well as operations of orders that have arrived in the meantime are scheduled in each case, too.

Fig. 6*a*–6*c* illustrate the average values of the performance measures collected in investigation I2 for the chosen factor levels. Due to interactions between the different factors,

a reasonable interpretation of the results obtained by the analysis of variance and multiple comparisons seems not possible. Based on this, a further decomposition of the analyzing model is required. An important result of this decomposition is the insight that average values that seem to be different in Fig. 6*a*–6*c* are actually significantly different.

The diagrams in Fig. 6*a*–6*c* reveal that the span between extreme values of the considered performance measures with respect to I2 (reactive strategies) is considerably larger than the span between extreme values with respect to I1 (preventive strategies).

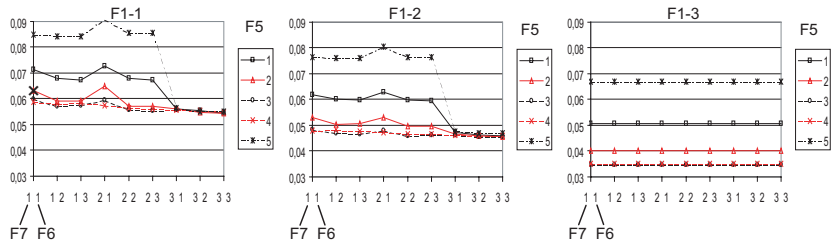

Figure 6*a*: Average proportion of setup times U^S of the total capacity

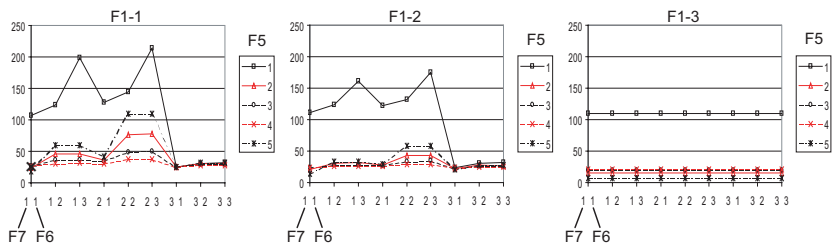

Figure 6*b*: R (mean tardiness)

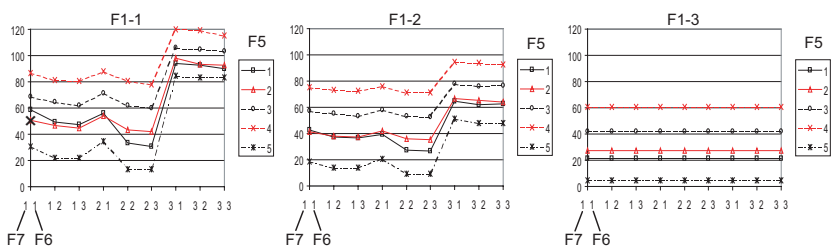

Figure 6*c*: Average values of the instability measure η

In Fig. 7 the percentage changes of the sampled performance measures compared with the sampled measures for the production system that is assumed to be given and that has to be improved are charted. Deteriorations are represented by positive values, ameliorations are represented by negative values. Thereby, in support of a better perceptibility of the diagrams in Fig. 7, they are chopped off at a moderate level of positive values of the performance measures. To some extent these values become extremely high. The applied performance measures in I2 are in accordance with I1 (the measures U^S, R and η respectively ΔU^S, ΔR

and $\Delta\eta$ as well as the combined performance measure SRI). The production system which should be improved is characterized by the factor levels F1-1, F5-2, F6-1 and F7-1.[7]

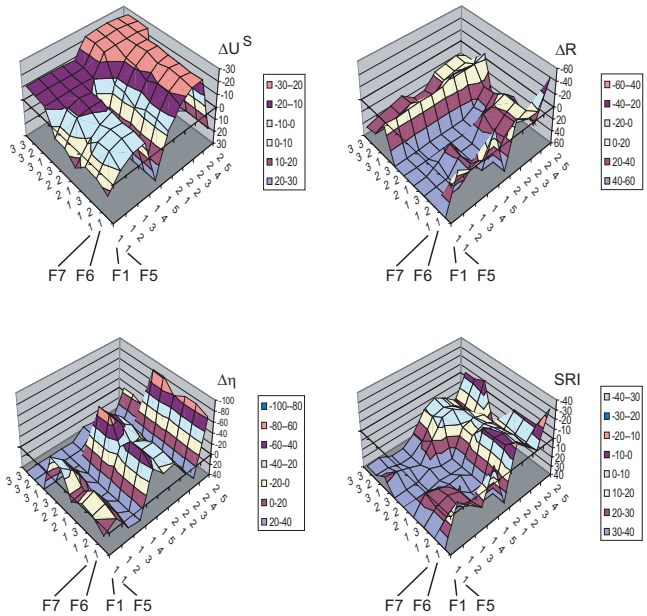

Figure 7: Percentage changes of the performance measures U^S, R and η as well as values of SRI

Fig. 7 depicts that the same strategies for managing disruptions are assessed differently in terms of the considered performance measures. The effects can vary considerably, and to some extent there are antithetic effects. Furthermore, the effect of one action for dealing with disruptions depends on other actions that may be taken into account. This can be seen from the jagged surface of the diagrams in Fig. 7. Moreover, the diagram for the combined performance measure SRI is jagged, too. However, due to the antithetic effects of the considered measures the average of their percentage changes that is represented by SRI is to some extent at a lower level than the percentage changes of the individual performance measures.

As a result of investigation I2 it can be stated that the investigated performance measures can be improved by applying reactive strategies. It should be kept in mind that there might be an amelioration with regard to one performance measure and a deterioration with respect to another one. In this context the performance measure regarding the planning instability that has not received attention in an appropriate manner so far deserves special mentioning. Investigation I2 reveals that without taking the instability measure into account several strategies for managing disruptions may be assessed as preferable, but the same strategies would be refused in consideration of the planning instability. Consequently, for assessing reactive strategies the application of only one performance measure should be avoided.

[7] In Tab. 2 these factor levels are underlined, in Fig. 6*a*–6*c* they are marked with "×". Fig. 7 does not contain a presentation of the effect that disruptions are completely eliminated (F1-3) because this case is merely hypothetical.

6 Conclusions

In this paper we have described some ideas for developing simulation models to manage disruptions in specialized production systems. As an example we considered a hybrid flow shop problem and performed two comprehensive simulation studies. The first refers to preventive strategies for managing disruptions. It shows that taking one or more actions having a direct impact on disruptions affect different performance measures (efficiency and instability measures) in the same way and independently from other operational conditions. If one procedure for managing disruptions improves one performance measure, other measures improve, too. That is, ameliorating the investigated production system is possible. The homogeneous effect on the different performance measures facilitates a decision with respect to an appropriate preventive strategy for managing disruptions. It enables an evaluation with only one combined performance measure that comprises the other individual efficiency and instability measures.

The second investigation deals with different reactive strategies. It exposes that varying the process of scheduling in a failure prone production system leads to a noticeable enhancement of several performance measures. However, an enhancement of one performance measure may also lead to a degradation of another one. This implies that selecting a specific strategy without taking into account the different performance measures or only taking into account one combined performance measure may lead to poor results. One important example relates to instability measures. A specific strategy would be rated as favorable if only the efficiency of capacity utilization and order processing are taken into account, but the same strategy would be refused in consideration of planning instability provoking an extra burden on the production schedulers.

Furthermore, due to the inconsistent effects of the examined reactive strategies for establishing an appropriate strategy for managing disruptions these strategies necessitate to investigate the contemplated strategies to a greater extent than the preventive strategies. This is enforced by their property that altering a reactive strategy may result in substantial changes of the recorded performance measures. In spite of these drawbacks of the investigated reactive strategies, there is the benefit that rearranging the scheduling process is easier than directly affecting the disruptions in connection with preventive strategies.

Sure enough, the investigated production system as well as the studies themselves are based on quite restrictive assumptions. For more general statements further studies and ideas need to be conducted. This is not only a problem in the area of production planning and control and consequently it should be regarded as a motivation for appropriate research activities. With respect to the hybrid flow shop it might be of interest to extend the ideas presented in this paper to more general scheduling environments as well as to (various extensions of) the resource constrained project scheduling problem.

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