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POTENTIAL OF DATA-DRIVEN SIMULATION-BASED OPTIMIZATION FOR ADAPTIVE SCHEDULING AND CONTROL OF DYNAMIC MANUFACTURING SYSTEMS

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ABSTRACT

The increasing customization of products, which leads to greater variances and smaller lot sizes, requires highly flexible manufacturing systems. These systems are subject to dynamic influences and demand increasing effort for the generation of feasible production schedules and process control. This paper presents an approach for dealing with these challenges. First, production scheduling is executed by coupling an optimization heuristic with a simulation model. Second, real-time system state data, to be provided by forthcoming cyber-physical systems, is fed back, so that the simulation model is continuously updated and the optimization heuristic can either adjust an existing schedule or generate a new one. The potential of the approach was tested by means of a use case embracing a semiconductor manufacturing facility, in which the simulation results were employed to support the selection of better dispatching rules, improving flexible manufacturing systems performance regarding the average production cycle time.

1 INTRODUCTION

The scheduling and control of production processes have great influence on the performance of manufacturing systems. In order to generate efficient processes, many decisions have to be made, e. g. the assignment of jobs and material to machines or sequences for the processing of jobs. However, the increasing customization of products requires that these systems handle higher numbers of product variants along with decreasing lot sizes, so that manufacturing systems become more and more complex. Therefore, the efficient management of these systems requires reliable methods for the scheduling of all processes and for the allocation of resources related to the system. It is tried to tackle these scheduling tasks with optimization techniques such as mixed-integer programming (Mula et al. 2010). However, even though the algorithmic power of solvers for this type of problem formulation improved during the last decades, most real manufacturing systems are too complex to be modeled and solved without ample simplifications, i. e. computing a solution is not feasible or takes more time than it is acceptable in practice. Hence, software systems are usually divided into separate modules for the computation of a basic schedule (ERP systems) and for the control of processes on the operational level (MES). In most cases, a mathematical optimization is only done within the basic schedule, while the shop floor control is performed on the basis of simple, static dispatching rules. This setup enables the generation of schedules within short computation times. However, in general, this approach does not generate optimal schedules that take the current state of the production system into account.

Production systems are embedded in dynamic environments. Their management is challenged by the complexity of production and transport networks as well as by the occurrence of disturbances. Dealing with these characteristics requires high levels of operational flexibility (Wiendahl and Breithaupt 1999). Production systems are subject to a wide range of dynamic influences from inside or outside, which induce relatively quick and unforeseen changes, such as machine breakdowns, delays or high-priority orders that were not anticipated. Due to the high degree of interdependencies between processes within production systems, disturbances can accumulate, so that even small changes of system parameters can have a big impact on the performance of the system (Prabhu and Duffie 1999). For instance, an increased production time on one machine due to wear of a tool can lead to delays that might impose delays in all subsequent production steps. This poses big challenges for an optimized scheduling of processes. Once there was a change of the system state, a previously computed schedule might be inefficient or even infeasible in the new situation, e. g. if a machine that was scheduled with urgent jobs is not available any more.

In addition, manufacturing systems feature a wide range of stochastic influences. This holds especially for tasks performed or influenced by human workers, where the duration of fulfilling a task varies, e. g. depending on the worker's capability level. However, this also concerns automated tasks, such as grinding processes, where the duration might depend on the specific surface of the work piece or the wear of the tool. Thus, some variables of the scheduling problem cannot be regarded as fixed and known values but have to be expressed in terms of a probability function. In literature, it is suggested that complex stochastic problems can be solved appropriately by simulation-based optimization (SBO) (Ge et al. 2014, Lin and Chen 2015). This approach combines the power of optimization heuristics with the advantages of simulation models, which can evaluate the effect of parameter changes even in very complex systems. These changes imply a modification of the simulation model, which represents the real system in the optimization setup. In the worst case, the real system changes so quickly that the simulation model always has to be modified before the optimization has finished. Such situations cannot be handled by traditional SBO methods, which are not designed for changes in the simulation model during optimization (März et al. 2011).

The increasing use of sensor-equipped collaborating machines, often referred to as "Industry 4.0" (Lee, Bagheri, and Kao 2015, Wang, Törngren, and Onori 2015) enables the collection of data about the current system state in real-time, for example physical positions of resources (raw material, load carriers, etc.) and the current state of machines (e.g. availability, error messages or pending need for maintenance), which can be used for the creation of realistic optimization models. This pulls the optimization from the basic scheduling level closer to the real processes and holds the potential to provide flexible and immediate reactions on dynamic changes of the production system, which is still very challenging for existing scheduling methods. SBO is a powerful tool for solving complex stochastic problems because of an insertion of a simulation model into the objective function of the optimization. Yet, traditional SBO approaches are not suitable for solving dynamic optimization problems. To make the potential of SBO techniques available to the scheduling of dynamic production systems, this paper describes a concept for the development of a new data-driven SBO method allowing changes of the simulation model during the optimization. The remainder of this paper is structured as follows. First the state of the art is detailed, covering: optimized scheduling of manufacturing systems, simulation of manufacturing systems, combination of simulation and optimization in manufacturing systems as well as information technologies supporting the scheduling and control of manufacturing systems. Subsequently, the data-driven simulation-based optimization approach for the adaptive scheduling and control of dynamic manufacturing systems is described. Then, a use case embracing a semiconductor manufacturing facility, where the simulation results were employed to support the selection of dispatching rules, is described. The paper closes with conclusions and suggestions for future research work.

2 LITERATURE REVIEW

2.1 Optimized Scheduling of Manufacturing Systems

Scheduling can be defined as the assignment of a number of jobs, which have to be performed within a certain period of time, to the available resources (machines, tools, and workers) of a production system (Ge et al. 2014, Jungwattanakit et al. 2008). A solution of a scheduling problem is an optimal schedule, which determines for each job at which time it is processed by which resources. The optimization criteria can vary according to the application. In some cases, it might be necessary to keep idle times as short as possible or to treat specific jobs with priority while others are not time critical. Scheduling is regarded as an integral component of short time planning (Quadt and Kuhn 2007) and can have large impact on the behavior of the production system regarding the adherence to due dates. Most scheduling problems, especially those emerging from real-world scenarios, belong to the class of NP-hard optimization problems. Thus, optimal solutions often cannot be computed or only in extremely long computation times. This is the reason for the extensive use of heuristic methods, which cannot guarantee optimal solutions but are often able to generate near-optimal solutions in relatively short computation times (Papadimitriou 2003).

One of the simplest heuristic scheduling methods is the use of dispatching rules, which means that each job in the queue of a machine is related with a priority value according to some predefined criteria, for example the time that is left until its due date. Then, whenever a suitable machine is available, the job with the highest priority is chosen for the next production step (Gondek 2011). Dispatching rules are characterized by a low effort for application and implementation and are therefore often used. They generate quite tight schedules and prevent idle times of machines. However, it is not suitable to represent complex restrictions of a production system (Morton and Pentico 1993). A more sophisticated approach, which offers more flexibility, is the use of evolutionary algorithms such as genetic algorithms. Genetic algorithms are able to compute solutions also for larger instances of combinatorial problems. However, they also feature limitations like the dependence on the choice of several parameters and the possibility to converge towards local extrema (Jungwattanakit et al. 2008). Evolutionary algorithms were applied to solve many different problems in production and logistics, such as the integrated scheduling of production and transport systems (Hartmann et al. 2013), the optimization of model-parameters for forecasting customer demands (Kück and Scholz-Reiter 2013) or the design and selection of dispatching rules (Freitag and Hildebrandt 2016).

The scheduling of manufacturing systems is a challenging task even for deterministic problems, i. e. all parameters such as the processing times of machines are known exactly. In reality, however, manufacturing systems feature uncertainty and stochastic events. In literature, this is addressed by dynamic scheduling approaches, which can be divided into proactive and reactive approaches or a combination of both. Proactive scheduling is often used when the uncertainty can be quantified in some way, so that stochastic events, which could occur during the execution of the schedule, can already be taken into account by the schedule. This might be achieved by introducing idle times between jobs (Mehta and Uzsoy 1999), which can lead to robust schedules but features the risk of low machine utilization and uncompetitive lead times if the idle times are chosen too long. Other approaches assume known probability distribution functions for a prediction of disturbances (Janak, Lin, and Floudas 2007), which require a precise knowledge of the manufacturing system. Reactive scheduling approaches intend to react on the actual occurrence of disturbances. This can be realized, for example, by the previously described dispatching rules if the schedule is not computed beforehand, but decisions are done at several local decision points in real-time (Van de Vonder et al. 2007). However, in order to achieve optimal decisions from an overall perspective, this approach results in another optimization problem, which is the choice of the best rule for each decision. Proactive and reactive scheduling can also be combined to hybrid strategies, which consist of two phases: First, a robust schedule is computed. Then, during the execution of the schedule, it is observed if disturbances occur, which exceed the tolerance of the schedule and make a rescheduling necessary (event-driven rescheduling policy) or a rescheduling is triggered periodically after a certain time interval (rolling time horizon) or both (hybrid policy). Periodic rescheduling represents a discretization in time, allowing an alignment of the rescheduling points with the necessary time to compute the new schedule. At the same time, it yields the risk of a poor performance if critical disruptions occur between the rescheduling. The event-driven policy leads to good solutions if instability of the system due to frequent schedule regeneration can be prohibited (e. g. by a frozen zone of jobs that are already in the system). However, the computation times of the current optimization approaches are likely to be prohibitive (Ouelhadj and Petrovic 2008). Finally, optimization is only suitable if a complex system can be modeled by a simplifying abstraction.

2.2 Simulation of Manufacturing Systems

The complexity of most real-world systems is related to their stochastic nature as well as to a multitude of internal and external interactions. Historically, one of the most suitable ways to derive experience-based solutions to deal with real-world complex systems is through their modeling and simulation (Longo 2010). Simulation-based techniques can be used either to develop or to evaluate complex systems. Aspects like the physical configuration or operational rules of a system can be considered. Its applications have grown in all areas, assisting managers in the decision making process and enabling a better understanding of processes in complex systems (O'kane, Spenceley, and Taylor 2000). Simulation can already be used to study systems in the design stage (Banks et al. 2000). Thus, simulation models can be used both as an analytical tool for predicting the effect of changes to existing systems and as a design tool to predict the operational performance of new systems under varying circumstances. In the simulation process, the model represents the key characteristics, behaviors and functions of the selected physical or abstract system. Simulation models address 'what if' questions: What will likely happen over time and at which specific places if a particular design and/or operating policy are implemented? Banks et al. (2000) state that the model usually takes the form of a set of assumptions concerning the operation of the system, which are expressed in mathematical, logical and symbolic relationships between the system objects of interest. In this way, potential changes to the system can be simulated first to predict the impact on system performance.

2.3 Combining Simulation and Optimization of Manufacturing Systems

As stated above, simulation is a powerful tool for the analysis and evaluation of complex and stochastic systems, such as manufacturing environments (Lin and Chen 2015). However, it cannot guarantee the optimization of these systems with respect to one or more performance indicators (lead times, production costs, etc.). Optimization methods are mainly used if a complex system can be modeled by a simplifying abstraction. Hence, both approaches are individually limited in taking optimal decisions for complex and stochastic systems, such as the scheduling of manufacturing systems. A promising approach with the aim of combining the strengths of both is the so-called simulation-based optimization (SBO). In this setting, the simulation model is used as the objective function of the optimization and the optimization method determines the optimal configuration of parameters for the simulation (Krug et al. 2002). Since the simulation model represents the real system in detail, it is not always necessary to express all relations of parameters analytically in the optimization model, which reduces the computational effort. For example, a scheduling task can consist of defining assignments of jobs to machines and sequences of the assigned jobs on the machines. A simple schedule can be determined directly from the assignments of jobs to machines if the sequences are generated within the simulation model by dispatching rules. In this case, the number of optimization variables is decreased dramatically, so that schedules can be generated with less computational effort. In fact, most scheduling problems belong to the class of NP-hard problems (Lin and Chen 2015). Thus, the necessary computation time of the optimization decreases exponentially with the number of variables showing the great potential of SBO. The idea of combining optimization and simulation is studied since the beginning of this millennium (Fu 2002) and has proven potential in practical applications of production and logistics systems (März et al. 2011). However, current approaches are limited to scenarios without dynamic influences; i. e. the simulation model does not change during the optimization. In fact, manufacturing environments are highly dynamic, so that an appropriate representation of the current system state requires an adaptation of the approach as it is explained in this paper.

2.4 Information Technologies Supporting Scheduling and Control of Manufacturing Systems

The use of information technologies has influenced different aspects of manufacturing. Specifically, manufacturing execution systems (MES) are information systems that interact directly with the physical production and exchange information with enterprise resource planning (ERP) systems (Qiu and Zhou 2004). MES provide an information hub to several other software systems for different management tasks and can also overlap with outer manufacturing system types (MESA 2016). Fast reaction regarding the scheduling of machines and operators is beneficial for a company, allowing it to handle disturbances (Aytug et al. 2005). Thus, the MES is a critical part to deal with uncertainty. Proper communication and computation methods implemented in these software systems are essential to allow for appropriate reactions. To improve the competitiveness of manufacturing, Lee (2003) proposed a concept called e-manufacturing, explaining the relation between different software systems and tools employed by enterprises: data and information transformation tools, prediction tools, optimization tools and synchronization tools. Advances in technology have led to an explosive growth in the amount of manufacturing data available, allowing for the creation of virtual representations of factories. In this context, the term 'Industry 4.0' refers to the creation of 'Smart Factories' by integrating the 'Internet of Things' (IoT) as well as 'Cyber-Physical Systems' (CPS) into the manufacturing process (Hermann et al. 2016). Similar concepts can be found in the scope of the term 'Smart Manufacturing' (Esmaeilian, Behdad, and Wang 2016). Modeling and simulation of the emerging real-virtual manufacturing systems can support diagnostic analytics in multiple ways. For instance, simulation optimization schemes enhance prescriptive analytics by relating input settings and goal performance (Shao, Shin, and Jain 2014). By considering the increase in current systems' complexity, Juan et al. (2015) argued for the relevance of extending metaheuristics based on simulation, so that they are capable of properly solving stochastic combinatorial optimization problems. Laroque et al. (2012) developed a fast converging procedure that combines particle swarm optimization and genetic algorithms in order to find suitable parameter configurations in a material flow simulation concerning layouts of the production system of an automotive supplier. For dealing with a huge search space, multi-objective, and high-variability problems, Lee et al. (2008) proposed the combination of evolutionary algorithms and simulation for performance estimation. Lanza, Haefner, and Kraemer (2015) applied an approach to optimize the performance of selective and adaptive assembly systems by virtually mirroring the real production system of stator assembly for an electrical drive in a discrete-event simulation. In a complemental direction, Wang et al. (2016) proposed the integration of industrial networks, data clouds, and supervisory control terminals with shop floor agents cooperating by means of negotiation mechanisms. Frazzon et al (2013) explored the context-dependent behavioral aspects related to the human stakeholders in CPS, using simulation to analyze their potential implications.

The data collected by the new technologies allows real-time information about the current state of a production system, which can be used to generate an up-to-date simulation model of the physical system. Promising approaches for the coupling of simulation models with real-time data acquisition are symbiotic simulation, online simulation and dynamic data driven application systems (DDDAS) (Aydt 2009). The paradigm of symbiotic simulation focuses on a close relationship between a simulation model and the corresponding physical system. States of the physical system are measured in real-time by sensors. The simulation model benefits from the real-time data, while the physical system may benefit from the effects of decisions made after simulation. Symbiotic simulation can be applied in various domains, such as semiconductor manufacturing processes, which involve a large number of processing steps and many different machines (Aydt 2009). A similar but less precisely defined concept is online simulation. It is characterized as the application of simulation to make decisions in near real-time. Additionally, it sometimes also refers to the property that the simulation model runs in parallel with the physical system (Aydt 2009). Another related concept is dynamic data driven simulation, characterized by simulation models, which are continuously influenced by real-time data streams (Hu 2011). All the mentioned overlapping concepts couple a simulation model with the consideration of current physical system states in order to analyze the system under study and predict its behavior. However, to make use of their potential for making quick and improved decisions, they need to be integrated into an optimization framework. The proposed approach intends to complement the research in this field by developing a data-driven simulation-based optimization method enabling the scheduling and control of highly dynamic manufacturing systems.

3 DATA-DRIVEN SIMULATION-BASED OPTIMIZATION APPROACH

The data-driven simulation-based optimization (SBO) method is designed to schedule complex stochastic and dynamic manufacturing systems (Kück et al. 2016). Figure 1 shows, in the bottom box, an abstraction of a small job shop scenario, which can be regarded as a network of machines processing material according to a given sequence of manufacturing steps. A given set of jobs can be performed by the execution of a schedule, which can be computed in a way that specific performance indicators are optimized (e. g. lead times or production costs). The actual execution of tasks by the machines is controlled locally on the process level (bottom box), for example by a manufacturing execution system (MES). However, as explained above, the generation of optimal schedules requires an optimization of certain decisions from an overall perspective. This can be decisions, which are part of the actual schedule (e. g. assignments of jobs to machines) or which support the control of the material flow (e. g. the optimal choice of dispatching rules for machines). Due to the nature of manufacturing systems, this is a complex stochastic optimization problem. A powerful approach for this type of problem is SBO, as shown in the upper box in Figure 1. However, manufacturing systems are also subject to external influences making their behavior dynamic, so that the actual process frequently differs from the plan. In this case, an adapted or a completely new schedule is necessary. If the computation of a new schedule takes a longer time period, then, in the worst case, it might occur that the actual system always changes before a schedule can be generated. Hence, in this setting, traditional SBO approaches as described above are not suitable.

Therefore, the first task of this approach is to expand the idea of SBO and develop an SBO method that allows continuous changes of the simulation model representing the current state of the manufacturing system. Due to the complexity of scheduling problems, even heuristic methods can lead to longer computation times in real-world applications. Since the number of optimization variables, and thus the computational effort, grows very fast with the problem size, i. e. the number of jobs and machines to be scheduled, it would be highly beneficial if a part of the schedule is already known and only a subset of variables had to be determined. Thus, a heuristic method is suggested that reduces the scheduling effort after a change of the real system by using parts of a previously known schedule. The basic idea behind this approach is that a change in the system might make the fulfillment of a whole schedule impossible. However, this does not mean that all resource allocations and decisions about sequences are not valid anymore. Hence, the proposed heuristic optimization method preserves valid information from before the system change and can this way continuously adapt to it. The second task is the development of a data exchange platform as it is indicated in the middle box of Figure 1. On the one hand, this comprises an automated aggregation of relevant system data for a permanent adjustment of the simulation model according to the current system state, so that changes of the production system are transferred directly into the simulation. It uses the fact that the availability of system data currently increases due to the introduction of cyber-physical systems in production environments. These systems combine the ability to collect and communicate sensor data. This can be used to access the state of a production system in real-time, e. g. information about workloads or availability of machines.

On the other hand, the data exchange platform is used to feed scheduling decisions and control instructions back to an existing manufacturing execution system. Only the availability of both, an SBO method allowing changes of the simulation model as well as a permanent transfer of the current system state into the simulation model, enables the setup of Figure 1 as a continuous loop for the scheduling and control of dynamic manufacturing systems. This will result in a new data-driven adaptive SBO method for a better management of dynamic influences in the scheduling and control of job shop manufacturing systems.

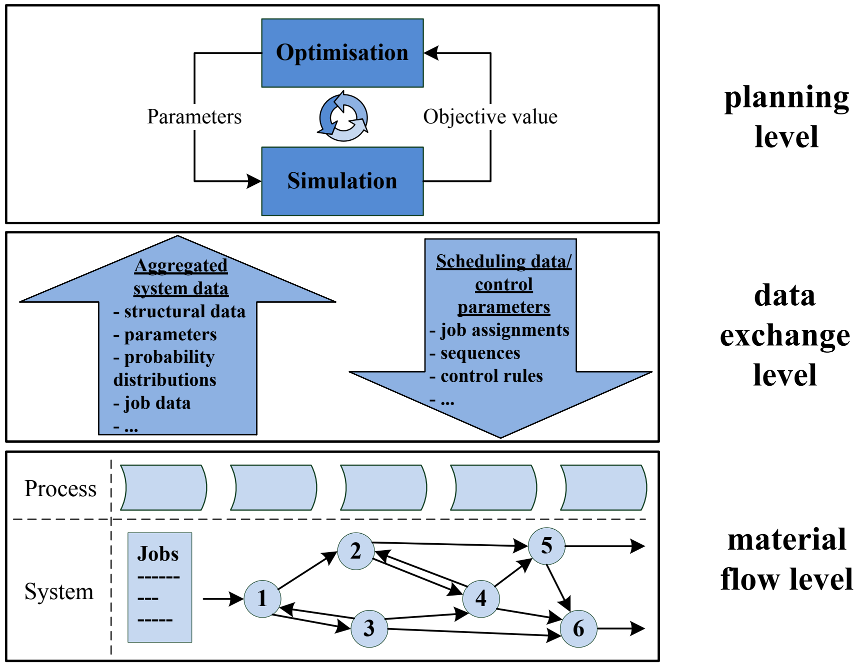

Figure 1: Data-driven simulation-based optimization approach for the adaptive scheduling and control of dynamic manufacturing systems (based on Kück et al. (2016)).

4 USE CASE

4.1 Description and Experimental Setup

For the use case, the FAB6 model from the publically available MIMAC (Measurement and Improvement of Manufacturing Capacities) testbed (Fowler and Robinson 1995, Feigin, Fowler, and Leachman 1996) was used. This scenario was also used in other research, e. g., by Zhou and Rose (2011) as an evaluation scenario for manually developed improved dispatching rules or by Hildebrandt, Goswami, and Freitag (2014) to automatically create improved dispatching rules using advanced simulation-based optimization. The model represents a semiconductor manufacturing facility with the following characteristics: nine process flows/products having between 234 and 355 operations, 104 tool groups with a total number of 223 machines including batch machines with sequence-dependent setup times, random machine downtimes (failures and maintenance). The simulation of the system was run for a total duration of 18 months, ignoring data from the first 6 months to focus on the system's steady state behavior. About 3800 jobs/lots are started during the 18-month period used for a simulation run. To implement this model the jasima simulation library (jasima - an efficient Java Simulator for Manufacturing and Logistics; http://jasima.net) was used. For the test case, both the duration and time between downtimes were given using an exponential distribution. All other model parameters, especially job arrivals, were deterministic. The product mix and bottleneck utilization resembles the settings from Zhou and Rose (2011). The results presented in this paper are the averages over 30 independent replications for each of the settings investigated.

In our empirical study, we applied specific parts of the data-driven simulation-based optimization approach summarized in Figure 1 to motivate the applicability of the concept. Since manufacturing systems are highly dynamic, this study dealt with different approaches to improve production scheduling in the case of dynamic events, such as machine failures. At first, the impact of machine failures on the performance of dispatching rules to schedule the jobs in the described MIMAC scenario was studied. A scenario with different selections of dispatching rules was simulated and examined whether different dispatching rules should be selected if the number of available machines within a tool group decreases. With the goal of minimizing the average production cycle times of all different products, one of the following standard dispatching rules (Haupt 1989) had to be selected: FIFO (first in first out), EDD (earliest due date first), FASFS (first arrival in system first served), CR (critical ratio), ODD (operational due date), SPT (shortest processing time first) and MOD (modified operational due date). To distinguish between jobs with the same priority, the FASFS rule was used as a tie breaker. As some machines require setup times, all of these rules were used with a setup-avoidance strategy, improving cycle times considerably. The batch machines used the "largest batch first" procedure forming a batch as large as possible for each batch family. Then the largest of these batches was started. If there was a tie, it was resolved by selecting the batch family of the job with highest priority. Secondly, to investigate the potential of real-time information about the current system state within a data-driven approach, the selection of the best dispatching rule based either on real-time information about machine failures or on the last known system state were compared.

4.2 Experimental Results

In order to analyze the impact of machine failures on the selection of dispatching rules, we determined the average cycle times of all jobs within the simulation time of 12 months for the seven different choices of dispatching rules and ranked the dispatching rules according to the average cycle time. For this purpose, the influence of machine failures within tool group "LTS-2", which consists of five parallel machines, was investigated. In this scenario, failures can cause that temporarily only four or three of these machines are available. Table 1 shows that in the case of no machine failures, the MOD rule achieves the lowest average cycle time per job of 24.92 days. In addition, Table 2 shows the differences of the average cycle times achieved by the other six dispatching rules compared to those achieved by the MOD rule.

Table 1: Average cycle times (in days) of all different jobs within the simulation time of 12 months for the seven different dispatching rules and different numbers of available machines in machine group "LTS 2" as well as ranks of the dispatching rules according to achieved cycle times for the cases with and without including machine failures into the simulation. Values in brackets show twice the standard error across the 30 independent replications conducted.

Dispatching rule	Average cycle times [days] / Rank for the case	
	with machine failures	without machine failures
MOD	27.98 (±0.61) / 3	24.92 (±0.08) / 1
ODD	27.12 (±0.14) / 1	24.93 (±0.08) / 2
CR	27.29 (±0.09) / 2	25.69 (±0.07) / 3
FCFS	29.40 (±0.18) / 4	26.06 (±0.11) / 4
SPT	32.99 (±0.31) / 7	26.66 (±0.12) / 5
ESS	31.99 (±0.19) / 5	27.87 (±0.13) / 6
FASFS	32.14 (±0.19) / 6	28.05 (±0.16) / 7

If machine failures are included into the simulation, obviously, the average cycle times increase for all selections of dispatching rules. However, the MOD rule is not the best rule any more, but only the third best of the seven possible choices of dispatching rules. Now, the CR rule and the ODD rule perform better. The ODD rule achieves the best average cycle time, which saves 20.5 hours for each job on average in comparison to the MOD rule. This is a cycle time reduction of 3.1%, or a reduction of 5.9% of its reducible components, i.e., the sum of setup and waiting times. These results indicate that the dynamic nature of manufacturing systems, which was represented by the inclusion of machine failures into our exemplary simulation study, influences the selection of appropriate dispatching rules for improving production scheduling. The standard approach for scheduling the operations in the regarded scenario does not use real-time information about the system state. Hence, it selects a dispatching rule based on the last known system state and keeps it although machine failures occur, which could cause that other dispatching rules would perform better. Therefore, the MOD rule was selected due to the lowest average cycle time. On the other hand, including real-time information about machine failures into the simulation enables a better selection of a dispatching rule, considering dynamic influences. Hence, the use of real-time information leads to a selection of the ODD rule instead of the MOD rule. Using a data-driven approach including real-time information leads to a better performance of 20.5 hours in cycle time per job on average. Another advantage of considering real-time information is that a better prediction of the cycle times can be achieved, which leads to better agreements regarding delivery dates and due dates.

Table 2: Differences of the average cycle times (in hours) of all different jobs within the simulation time of 12 months and different numbers of available machines in machine group "LTS 2" for the comparison of the six other dispatching rules against MOD (the best rule for the case of no machine failures) for the cases with and without including machine failures into the simulation.

Dispatching rule	Difference of the average cycle time compared to those of MOD [h] for the case	
	with machine failures	without machine failures
MOD	-	-
ODD	-20.50	0.25
CR	-16.51	18.30
FCFS	34.11	27.24
SPT	120.22	41.72
ESS	96.20	70.85
FASFS	99.96	74.93

5 CONCLUSION AND OUTLOOK

This research paper described a data-driven simulation-based optimization approach for the adaptive scheduling and control of dynamic manufacturing systems. Within this approach, the scheduling is done by coupling an optimization heuristic with a simulation model to handle complex and stochastic manufacturing systems. The control task is addressed by a continuous adaptation of the simulation model using real-time data from the shop floor. If changes or disturbances occur, the simulation model and consequently the scheduling model is updated and the optimization heuristic adjusts an existing schedule or generates a new one. This approach uses real-time data provided by future cyber-physical systems to integrate scheduling and control and to manage the dynamics of highly flexible manufacturing systems. By means of a use case embracing a semiconductor manufacturing facility, the use of real-time data coupled with a simulation model to influence the choice of better dispatching rules for improving system performance regarding the average production cycle time was tested. The obtained results motivate the use of real-time information for improving production scheduling. Forthcoming research will embrace both the full implementation of the data-driven simulation-based optimization approach for the adaptive scheduling and control of dynamic manufacturing systems as well as the development of use cases.

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