Meta Heuristics for Dynamic Machine Scheduling: A Review of Research Efforts and Industrial Requirements

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Abstract: This paper presents a survey on the state-of-the-art of dynamic machine scheduling problems. For this purpose, 82 papers have been examined according to the underlying scheduling models and assumptions, the source and implementation of uncertainty and dynamics as well as the applied solution methods and optimization criteria. Furthermore, the integration of machine scheduling into the functional levels of a company is outlined and the essential requirements for dynamic machine scheduling in modern industrial environments are identified. On this basis, the most prevalent gaps, the main challenges, and conclusions for future research are pointed out.

1 INTRODUCTION

Machine scheduling aims at finding optimal assignments of production orders to machines for a given planning horizon under consideration of specific criteria and predefined constraints. As part of the operative planning process it plays a fundamental role in economic production. A decrease in lead time, for example, may result in a reduction of capital commitment costs of the producing company and therefore cause higher liquidity.

One main challenge in machine scheduling is the adequate modeling of the dynamic production environment and the ability to react to unforeseen events like unexpected machine failures, staff shortages, delayed material deliveries or urgent changes in customer orders. Due to major advances in information and communications technology, such as cloud computing, internet of things, and mobile computing, information on new customer orders, processing delays, machine failures or current material movements become ubiquitous (often in real time). Thus, modern machine scheduling algorithms are expected to be capable of including this information into the optimization process in an online fashion, thereby supporting more informed decisions.

Furthermore, classical structures of the automation pyramid are increasingly replaced by infrastructures of interlinked machines and systems. Embedded into such rapidly evolving industrial environments, the requirements for machine scheduling software are changing as well: more and more dynamic machine scheduling becomes a core asset for production planning, plant control and reactive decision making.

However, what are the essential requirements for dynamic machine scheduling in modern industrial environments? To what extent have such requirements previously been addressed by recent scientific work? Which are the most prevalent gaps, the main challenges, and conclusions for future research?

This paper aims to focus on these questions and is structured as follows: Section 2 presents a brief review on related work. Section 3 provides a problem definition and an overview on the state-of-the-art in dynamic machine scheduling approaches. Section 4 describes the information and communication technology (ICT) and current trends in industrial production environments and derives a set of consolidated requirements for machine scheduling software. In Section 5, the current state-of-the-art is evaluated considering its industrial applicability and further research directions are given. Finally, Section 6 concludes the paper.

2 RELATED WORK

The Machine Scheduling Problem (MSP) is a well-known problem in the field of combinatorial optimization problems and numerous papers were published on that topic in the last decades. For a detailed description of the MSP see (Pinedo, 2012). In addition, a

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range of survey papers have been published focusing on different aspects of the deterministic MSP. (Mokotoff, 2001), for example, gives a review on the Parallel MSP while (Allahverdi et al., 2008) focus on scheduling problems that include setup times or costs and (Ma et al., 2010) provide a survey on MSPs with deterministic machine availability constraints. A survey on non-deterministic problems is given by (Ouelhadj and Petrovic, 2008). While (Ouelhadj and Petrovic, 2008) mainly consider the solution techniques of dynamic MSPs like heuristics, meta-heuristics, multi-agent systems, and other artificial intelligence techniques in detail and give a qualitative comparison, this work focuses on their industrial application.

3 STATE-OF-THE-ART IN DYNAMIC MSPs

3.1 Problem Description

The classical machine scheduling problem consists of assigning n jobs of varying processing time to m machines in an optimal order due to one or more optimization criteria. Each job can contain a set of operations and a corresponding order of operations that usually originates from technical conditions of the producing company. In literature, there are five types of MSPs (see Table 1), which vary in the number of operations per job, the number and types of available machines and the sequence of operations. For more information on this classification of MSPs see (Graham et al., 1979).

Table 1: Types of MSPs.

Single MSP:	- one machine - one operation per job
Parallel MSP:	- several machines - one operation per job
Flow Shop	- several machines - several operations per job - equal sequences of operations
Job Shop	- several machines - several operations per job - different but specified sequences of operations
Open Shop	- several machines - several operations per job - no sequences of operations

Another criterion to categorize MSPs consists in whether dynamic aspects are integrated into the underlying model of the production environment:

- *Deterministic MSP:* exact information on all parameters (e.g. number of jobs, processing times, availability of material) is assumed to be available during the complete optimization process,
- *Non-deterministic MSP:* information on some parameters is not exactly known in advance, the actual information is revealed by the occurrence of the corresponding (dynamic) events.

3.2 Overview of Papers Reviewed

The state-of-the-art analysis comprises 82 papers working on non-deterministic MSPs. Hence, the underlying machine scheduling model contains at least one parameter exposed to uncertainty or dynamic changes or the optimization algorithm includes reaction mechanisms on dynamically occurring events. Even though the selection of the examined papers focuses on their topicality, research with earlier publication dates was also considered if it contained relevant contributions that were not addressed by more recent papers. The publication dates of the examined papers vary from 1996 until 2018. However, the vast majority was published in the last ten years as visible in Figure 1. For a complete overview of all examined papers and their features see Figure 10 in the Appendix.

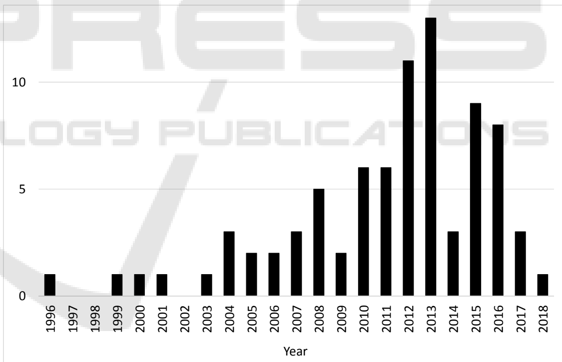

Figure 1: Publication dates of the reviewed research.

According to (Riezebos et al., 2010), the choice of a machine scheduling algorithm is mainly influenced by the chosen machine scheduling model and some basic assumptions, the optimization criteria and the applied solution method. Hence, these factors are examined more closely in the following.

3.3 Uncertainty and Dynamics

In deterministic MSPs, all relevant information on jobs and machines are available at all times and assumed to be accurate. Real production environments, however, contain uncertainties like dynamically incoming orders or unexpected machine failures which have big influence on the production plan. Hence, exact data is not available a priori. (De Snoo and Van Wezel, 2011) distinguish between four types of dynamic events as shown in Table 2.

Table 2: Types of dynamic events.

Urgent orders:	important orders, sample requests, complaints
Order changes:	change of amount/article/date, new orders, cancellations
Internal disturbances:	production/machine failures, delay, rework
Supplier problems:	delay in material provision due to external disturbances

Figure 2 shows their frequency in the examined literature. In about two thirds, only one dynamic event is considered, while one third includes more than one event. Uncertainty is thereby mainly modeled by the use of stochastic or fuzzy data. In case deterministic data is used, the occurrence of events is dynamically revealed to the optimization algorithm triggering responses in real-time or periodical updates of the production plan.

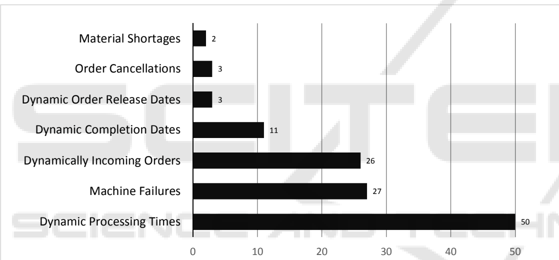

Figure 2: Frequency of dynamic events in literature.

A basic concept to categorize dynamic machine scheduling is to distinguish between offline and online scheduling. *Offline scheduling* means the creation of a schedule at the beginning of the planning horizon. Due to the dynamics of the production environment, there might emerge a need to update the production plan during its execution. This process is called *rescheduling*. In *online scheduling*, no production plan is created in advance but during execution. This enables the optimization process to respond directly to unexpected events. A more detailed classification of dynamic MSPs is given by (Renna, 2010) in Table 3. While online scheduling corresponds directly to *completely reactive* scheduling, offline scheduling is divided into three different categories. It is worth mentioning that some of the authors considering dynamic events do not explicitly specify the handling or the algorithmic reaction to those. Hence, not all of the examined research could be classified according to (Renna, 2010).

As also visible in Table 3, there are different ways

Table 3: Categories of dynamic machine scheduling.

completely reactive:	- no schedule created in advance - real-time scheduling
predictive reactive:	- schedule created in advance - rescheduling as real-time-response to dynamic events
robust predictive reactive:	- schedule created in advance - consideration of effect of events to a certain extent - rescheduling only if events influence performance significantly
robust pro-active:	- schedule created in advance - prediction of effect of events - no rescheduling

to implement rescheduling. It can be carried out periodically (e.g. at the beginning of each planning horizon or after fixed time intervals), it can be triggered by certain events, it can be a hybrid of the both or might be linked to the current production performance. Furthermore, there are two different types of rescheduling in the examined literature:

- *Schedule Repair*: only local changes are performed, global production plan is mainly preserved.
- *Complete Rescheduling*: generation of an entirely new production plan.

In general, complete rescheduling may lead to better optimization results but requires high computing time (Zandieh and Gholami, 2009). A further disadvantage of complete rescheduling is the fact that it can cause a destabilization of the production process by the lack of continuity in the production plan. This phenomenon is generally known as *Shop Floor Nervousness*. Moreover, machine scheduling is frequently linked to other business units such that broad changes in the production plan may also require a change of plans in the respective departments.

3.4 Model Assumptions

Machine scheduling models embody a broad range of different assumptions on the features of the MSP. As authors usually do not state all assumptions made, it is difficult to make general statements on their quantity. A list of the most common assumptions and the count of explicit occurrences is given in Figure 3.

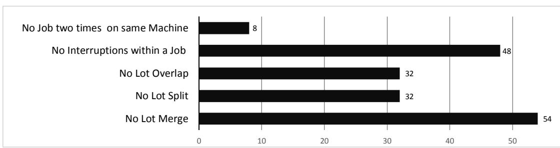

Figure 3: Most common assumptions in literature.

As the definition of lot sizes is usually done before machine scheduling, lot merge, split and overlap are frequently not included in research on MSPs. However, disturbances in the production process of an enterprise may cause postponements, which require a reduction of lean time. For a brief explanation see Figure 4.

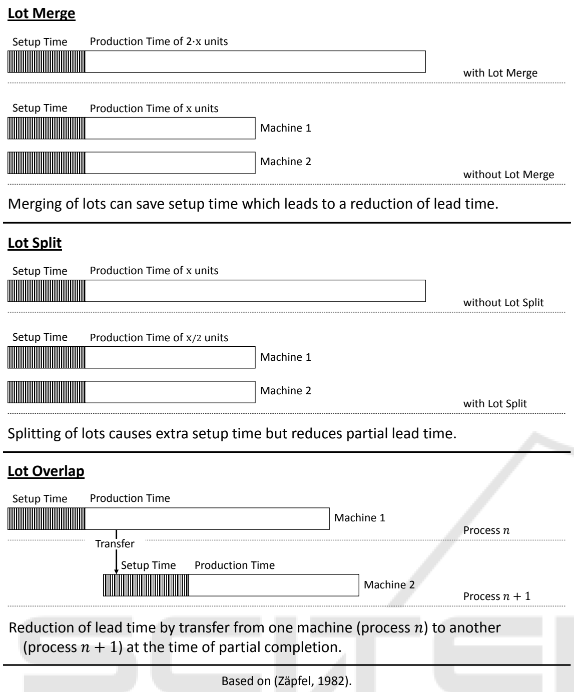

Figure 4: Lot merge, lot split and lot overlap.

Parameters like the capacity of interim storage or transport and setup times are often ignored or assumed to be irrelevant for the solution quality of the MSP. A few authors, however, include transport and setup time by adding it to the process time of the different operations. Assumptions on the interconnectivity of the production process and other business units are not mentioned.

3.5 Optimization Criteria

Previous publications also cover a wide range of different optimization criteria. While some authors focus on machine capacity and idle times, others consider the deviation to given due dates or economical variables. The most common optimization criterion in machine scheduling is the makespan, followed by tardiness as shown in Figure 5. It is evident that there is a strong focus on production-based criteria, while criteria that emerge from customer perspective or other that are important for the embedding of machine scheduling into the ICT infrastructure of the producing company (e.g. stability) are often omitted.

About 50% of the examined papers consider one

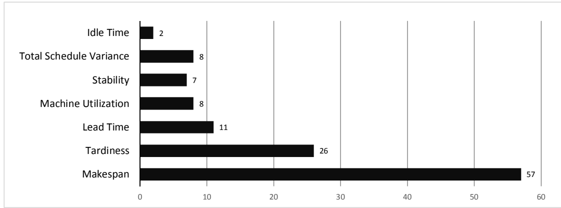

Figure 5: The most commonly used optimization criteria.

optimization criterion only. If more criteria are taken into account, they are mainly modeled and processed as weighted sum or as Pareto fronts.

3.6 Solution Methods

In the examined literature different approaches were used to tackle the dynamic MSP, most of them inspired by nature or biology, like Evolutionary Algorithms (EA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO) or Simulated Annealing (SA). Furthermore, Priority Dispatching Rules (PDR), Variable Neighborhood Search (VNS), Estimation of Distribution Algorithms (EDA), Teaching-Learning Based Optimization (TLBO) and Tabu Search (TS) are used to tackle the MSP (see Figure 6). It is noticeable that more than half of all authors use evolutionary algorithms. This might result from the fact that EA are very adaptable to dynamic environments.

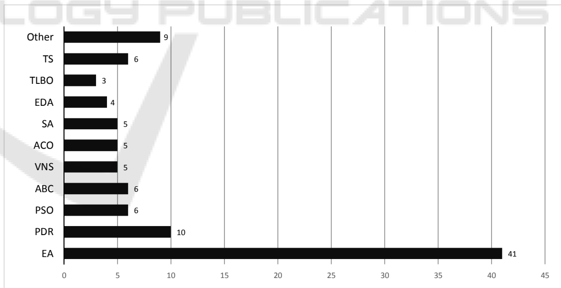

Figure 6: Solution methods for the dynamic MSP and their count in the examined literature.

4 INDUSTRIAL ENVIRONMENTS AND REQUIREMENTS

4.1 ICT in Industrial Environments

Ideally, the planning process of a company would include all business functions as well as its whole life cycle. However, this approach leads to models with such high complexity, that it is not possible to calculate solutions within reasonable time (Buzacott et al., 2013). For this reason, a company is divided into functional levels and sectors, each with different scope of planning and different planning cycles. For the functional levels of a company, refer to Figure 7.

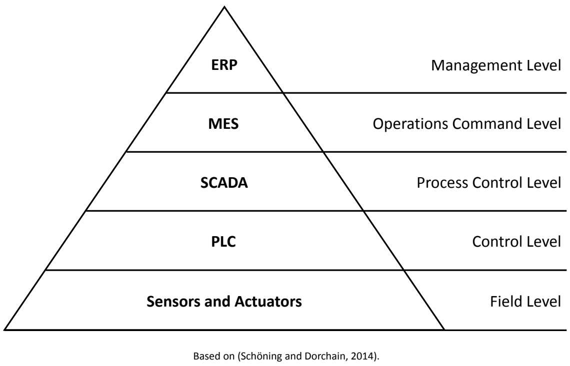

Figure 7: Conventional automation Pyramid.

At first, Enterprise Resource Planning systems (ERP systems) are applied for the cross-functional coordination of the individual functional areas of a company. ERP systems enable a central planning for the production and other sectors such as marketing, accounting, finance, materials management, human resources and quality management on the basis of a common information system (Buzacott et al., 2013). For operative production planning and controlling, Manufacturing Execution systems (MES systems) are applied on the operations command level. On that level, machine scheduling is executed. Supervisory Control and Data Acquisition systems (SCADA systems) are located on the process control level to ensure the monitoring and steering of technical processes (Heinrich et al., 2015), while programmable logic controllers (PLC) are placed on the control level to transmit the process information to higher-level systems and to enable the automatic control of the plant and machinery (Seitz, 2015). Sensors and actuators are located on the field level and are connected to PLC. While sensors are responsible for the data collection, the processes are controlled with the help of actuators (Settelmeyer, 2007).

Machine scheduling can be carried out using a MES system, as it serves as a link between the management level and the shopfloor (Heinrich et al., 2015). On the one hand, the MES system receives production orders from the ERP system (Gutenberg, 1971). On the other hand, the MES systems gets feedback data from the shopfloor such as status and time information, production volumes, consumption messages, occupancy time as well as disturbances (Seitz, 2015). According to (Schuh and Stich, 2013), the data availability is elementary for machine scheduling: if the scheduling and rescheduling are based on insufficient data, this leads to inaccurate results. The current challenge of the ICT is the data transmission which is hampered due to the hierarchical structure of any enterprise and the different linking possibilities of the information and communication systems. For an extract of the linking possibilities see Figure 8. (Schöning and Dorchain, 2014) specify machinery with different ages and origins as a reason for the diversity of the linking possibilities. Additionally, the heterogeneous IT-landscape which usually evolves over time is stated by (Schuh et al., 2007) as a recent challenge for planning and control approaches.

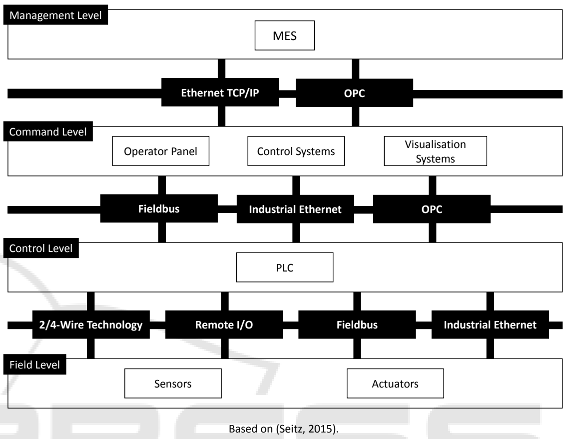

Figure 8: Linking possibilities.

4.2 Current Trends

Apparently, data from the shopfloor can be collected, but the data transmission is hampered due to the hierarchical structure with the different linking possibilities. According to (Nyhuis and Schmidt, 2017) a consistent data exchange can be ensured by avoiding media discontinuities. This can be achieved by establishing a decentralized network through introducing *cyber physical systems* (CPS), which communicate with each other via the internet (Bauernhansl et al., 2014). Due to their direct connection to the data streams of the field level and the networking with other objects, as illustrated in Figure 9, a decentralized network can be established (Schöning and Dorchain, 2014). Thus, the conventional automation pyramid and the associated challenges will be resolved (Höll and Stimming, 2015).

In addition to the consistent data exchange, CPS enable automatic data collection, whereby delayed feedback as well as possible wrong entries can be avoided (Reinhart, 2017). For this purpose, sensors are applied on workpieces, working stations and material containers (Höll and Stimming, 2015). For instance, the following information can be provided ba-

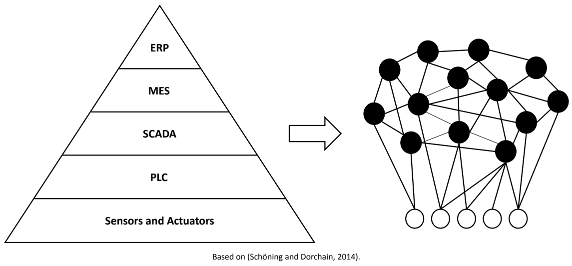

Figure 9: Dissolution of the automation pyramid.

sed on the collected data (Chongwatpol and Sharda, 2013):

- order status,
- waiting and processing products on a machine,
- machine set up,
- machine failures,
- material shortages,
- available and utilized machine capacity.

While sensors collect data, the aggregation, evaluation and the preparation of the data can be conducted using cloud computing (Reinhart, 2017). Therefore, cloud computing can serve as an integration basis (Reinhart, 2017) and enables the access to the required data from anywhere (Hauptvogel, 2015). Hence machine scheduling, production control as well as the maintenance or the materials management have access to a common database (Reinhart, 2017).

5 DIRECTIONS FOR FUTURE RESEARCH

In this section the current state-of-the-art in machine scheduling is evaluated and further research directions are given on three different levels. First of all, current scheduling models and optimization approaches are examined to increase their industrial applicability. Secondly, challenges concerning the integration of dynamic machine scheduling into the IT infrastructure of an enterprise are illustrated. Finally, human interaction with machine scheduling is discussed.

5.1 Scheduling Model

It is obvious that the value of machine scheduling algorithms for a company depends largely on the quality of the underlying model of reality. Scheduling models that are based on parameters that do not match the production environment of a given company or that do not include all of their required dynamic event types, are not applicable in real production scenarios. Hence, it is of great importance to represent production constraints such as existence and capacity of interim storage, setup and transportation times as well as the possibility of lot merge, split and overlap in case of production disturbances, which are hitherto mainly omitted in research, in an adequate way. Furthermore, even if all important types of events are covered in literature, it is necessary to consider them simultaneously as this portrays the conditions of real production environments.

As the success of a company is dependent on several different criteria like efficiency or customer-friendliness, another main challenge consists in identifying and representing them adequately by choosing the right (combination of) optimization criteria. Especially customer-driven criteria e.g. customer-based priority rules need to find stronger integration into machine scheduling. One criteria that finds little consideration in literature but is relevant for almost all enterprises is stability. A change of the production plan can cause a change of plans in other business units of the enterprise as well as a transition of resources, which might lead to not negligible extra costs. In particular, the complete rescheduling method, which is repeatedly applied in literature, can cause stability problems. Therefore, research on the correlation of rescheduling and stability, the inclusion of stability as optimization constraint or objective and a transparent description of its implications on other business units would be desirable. Moreover, existing approaches need to be evaluated on real data or reality-like benchmarks to lay the foundations for further improvements and proper adaption to real production environments.

5.2 System Level

As stated in Section 4, the advancement in sensor technology allows for real-time availability of different data representing the current state of the production process at any time. This information can be transferred to machine scheduling algorithms using cyber physical systems and cloud computing. However, ERP- and PPS-systems are currently not ready for the required networking due to their central and deterministic orientation. Moreover, an exchange of those systems will not occur in the near future (Ganschar and Gerlach, 2013). Hence, one main challenge consists in the evaluation of the consequences of dynamic machine scheduling on ERP-relevant data. Additionally, interfaces between machine scheduling and business units like resource planning or order and production planning have to be defined adequately.

5.3 Human Interaction

An application of machine scheduling algorithms without human interaction requires fully automatic recognition and processing of event data. According to a survey of the Fraunhofer Institute in 2013 (Ganschar and Gerlach, 2013), only few of the interviewed companies (16%) believe that the majority of the required event data for dynamic machine scheduling can be automatically identified by current technical systems, while 59% of the interviewed companies consider human abilities as important component (Ganschar and Gerlach, 2013). Furthermore, human knowledge is fundamental in modeling of production processes and adapting the parameters of the optimization model (De Snoo and Van Wezel, 2011). Human competency is also needed in decision making. To this day, human production planners have gathered huge expertise in choosing the best production plan according to the requirements of a company. With the ongoing progress in the area of artificial intelligence, it remains an open question, whether these tasks could be taken over by intelligent machines at some point. But even if that is the case, the acceptance of automatically generated production plans by human decision makers needs to be subject to further research (Hußlein and Breidbach, 2015).

6 CONCLUSION

In this paper, the state-of-the-art in dynamic machine scheduling and current directions in industrial production environments were presented. In the examined literature, a great number of optimization criteria and model assumptions could be identified. These have to be further developed and combined to match real production environments. The applied solution methods were found to be mostly nature-inspired. Statements on their quality were not part of this work. A big shortcoming was found in the fact, that only two of the approaches were tested and evaluated on real data. Thus, this needs to be intensified in future research. Furthermore, all important dynamic event types are covered in the examined literature. However, simultaneous consideration of several events types as well as adequate reactions and the respective influence on the stability of the production plan require further investigation. The hierarchical structure of the IT infrastructure in companies is a current obstacle in applying dynamic machine scheduling, as dynamic changes of the production plan can have influence on other business units and therefore also on other levels of the IT system. Prospectively, cyber physical systems and cloud computing allow for a decentralization of the automation pyramid and enable a steady exchange of data and real-time data availability, which can serve as a basis for the implementation of dynamic scheduling. Hence, one main challenge consists in defining adequate interfaces. Additionally, an empirical study could be conducted to further investigate the suitability of dynamic scheduling approaches for practical application. On the one hand, software manufacturers could be asked on the current state of dynamic machine scheduling in practice. On the other hand, software users could be consulted to identify practical problems and challenges of current machine scheduling.

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APPENDIX

For a complete overview on the examined papers and the respective features see Figure 10. As not all authors state every feature of their work or comment on each of the criteria defined in this survey, it is not remarkable that the table contains some blank lines.

Author(s)	Type of MSP					Uncertainty and Dynamics																						Assumptions					Optimization Criteria							Solution Method													
						Event Types							Model			Category					Rescheduling																																
	Single MSP	Parallel MSP	Flow Shop	Job Shop	Open Shop	Dynamic Processing Times	Machine Failures	Dynamically Incoming Orders	Dynamic Completion Dates	Dynamic Order Release Dates	Order Cancellations	Material Shortages	Stochastic Model of Uncertainty	Fuzzy Model of Uncertainty	Deterministic	Completely Reactive	Predictive Reactive	Robust Predicte Reactive	Robust Pro-ative	Not explicitly assignable	Event Based Rescheduling	Periodic Rescheduling	Performance-oriented Rescheduling	Online	Offline	Schedule Repair	Complete Rescheduling	No Lot Merge	No Lot Split	No Lot Overlap	No Interruptions within a Job	No Job two times on same Machine	Time of Production	Tardiness	Lead Time	Machine Utilization	Stability	Total Schedule Variance	Idle Time	Evolutionary Algorithm	Priority Dispatching Rules	Particle Swarm Optimization	Artificial Bee Colony	Variable Neighborhood Search	Ant Colony Optimization	Simulated Annealing	Estimation of Distribution	Teaching-Learning-Based Optimization	Tabu Search	Other	One Method	Hybrid	Parallel
Adibi et al. 2010				X			X	X							X		X				X				X		X	X	X	X	X		X	X										X							X		
Ahmadi et al. 2016				X			X								X		X				X				X	X		X			X		X				X			X											X		
Alcan and Basligil 2012		X				X								X						X					X			X			X		X							X											X		
Al-Hinai and El Mekkawy 2011				X			X						X					X			X				X	X					X		X				X			X											X		
Azadeh et al. 2012				X		X									X	X								X				X		X		X	X								X										X		
Balin 2011		X				X								X						X					X			X			X		X							X											X		
Behnamian 2014		X				X								X						X					X			X	X		X		X							X											X		
Bilkay et al. 2004				X			X								X		X				X				X		X						X	X		X														X	X		
Chen et al. 2012	X							X							X	X								X										X	X					X											X		
Chen and Ji 2007		X						X							X		X					X			X		X	X	X		X							X	X	X											X		
Choi and Wang 2012			X			X							X			X				X				X	X			X					X							X	X												X
Ebrahimi et al. 2014			X						X				X							X					X			X	X	X	X		X	X						X											X		
Fayad and Petrovic 2005				X		X			X					X						X					X			X						X						X											X		
Gao et al. 2015				X				X							X		X				X				X			X	X		X		X										X								X		
Gao et al. 2016a				X		X								X						X					X			X	X		X		X			X							X								X		
Gao et al. 2016b				X		X		X						X			X				X				X		X	X	X	X	X		X										X								X		
Gholami and Zandieh				X			X								X		X				X				X	X		X			X		X	X						X											X		
Ghrayeb 2003				X		X								X						X					X								X							X											X		
Gonzalez-Neira et al. 2016			X			X							X							X					X									X																X	X		
Gu et al. 2010				X		X							X							X					X			X			X	X	X							X											X		
Hamzadayi and Yildiz 2016		X					X	X							X		X				X				X		X						X													X					X		
Hao et al. 2013				X		X							X							X					X			X	X	X			X														X				X		
He and Sun 2013				X			X						X					X			X				X			X	X				X				X			X											X		
Horng et al. 2012				X		X							X							X					X			X	X	X	X							X		X											X		
Javadi et al. 2008			X			X														X					X			X		X	X	X	X																	X	X		
Kianfar et al. 2012			X					X							X					X	X	X			X		X	X	X	X	X			X						X	X											X	
Kundakci and Kulak 2016				X		X	X	X							X		X				X				X		X	X	X	X	X		X							X	X											X	
Kutanoglu and Sabuncuoglu 2001				X			X						X			X								X										X							X										X		
Lai and Wu 2011			X			X								X						X					X								X							X											X		
Lei 2010a				X		X								X						X					X			X	X	X	X		X							X											X		
Lei 2010b				X		X			X					X						X					X			X		X			X					X		X											X		
Lei 2011				X		X								X						X					X				X	X			X							X											X		
Lei 2012				X		X								X						X					X			X	X	X	X		X							X											X		
Lei and Xiong 2007				X		X							X							X					X			X		X			X	X						X											X		
Li et al. 2015			X			X	X	X		X	X				X		X				X				X			X		X	X		X				X											X			X		
Li et al. 2017				X			X	X			X				X		X				X				X			X	X		X		X										X						X			X	
Li and Pan 2013				X		X								X						X					X			X		X		X	X									X							X			X	
Liao and Su 2017		X				X				X				X						X					X			X			X		X												X					X		X	
Lin 2015				X		X								X						X					X			X	X	X	X		X							X											X		
Liu et al. 2005			X			X							X							X					X								X									X				X						X	
Liu et al. 2015				X		X	X	X						X			X				X				X		X		X		X		X														X				X		
Louis and Xu 1996					X		X								X		X				X				X		X						X							X											X		
Madureira et al. 2007				X		X		X	X	X	X				X		X				X				X	X														X									X		X		
Metan et al. 2010				X				X							X	X							X	X										X							X										X		
Mokhtari and Dadgar 2015				X		X	X		X				X							X					X			X			X			X												X					X		
Nakhaeinejad and Nahavandi 2013			X			X								X						X					X			X			X		X		X				X											X	X		
Nie et al. 2013				X				X							X	X								X									X	X	X						X										X		
Niu et al. 2008				X		X								X						X					X			X	X	X		X	X							X		X										X	
Noori-Darvish et al. 2012					X	X			X					X						X					X			X		X	X	X	X	X								X									X		
Palacios at al. 2015a				X		X								X						X					X						X		X							X										X		X	
Palacios at al. 2015b				X		X								X						X					X				X		X		X							X									X			X	
Petrovic and Duenas 2006		X										X		X				X			X				X								X																	X	X		
Qui and Lau 2013				X			X	X							X	X								X				X	X	X				X	X	X		X			X											X	
Rahmani and Ramezanian 2016			X					X							X		X				X				X		X				X			X			X							X							X		
Rajabinasab and Mansour 2011				X		X	X	X							X	X								X				X			X			X	X										X						X		
Rangsaritratsamee et al. 2004				X				X							X		X					X			X		X				X		X	X			X			X											X		
Reddy et al. 2018				X			X								X					X					X			X			X		X			X												X			X		
Renna 2010				X			X	X							X	X								X											X	X									X						X		
Sakawa and Kubota 2000				X		X			X					X						X					X			X	X	X			X					X		X											X		
Sakawa and Mori 1999				X		X			X					X						X					X			X	X	X								X		X											X		
Song et al. 2006				X		X			X					X						X					X			X	X	X	X							X		X					X							X	
Torabi et al. 2013		X				X			X					X						X					X			X			X			X	X	X						X									X		
Touat et al. 2017	X					X								X						X					X			X			X			X						X											X		
Vinod and Sridharan 2008				X				X							X	X								X				X	X	X	X	X		X	X						X										X		
Wang et al. 2013a			X			X	X						X			X				X				X	X			X		X	X		X								X					X							X
Wang et al. 2013b				X		X								X						X					X								X										X	X								X	
Wang et al. 2013c				X		X								X						X					X			X	X	X	X		X														X				X		
Wang et al. 2015			X			X							X							X					X								X							X							X					X	
Wu and Gu 2004			X			X			X					X						X					X				X		X	X	X					X		X											X		
Xia et al. 2016							X	X							X		X				X				X		X													X				X								X	
Xiang and Lee 2008				X			X	X							X	X								X										X	X	X									X						X		
Xiong et al. 2013				X			X						X						X						X			X		X			X	X						X											X		
Xu at al. 2015				X		X								X						X					X								X															X			X		
Yeh et al. 2014		X				X								X						X					X			X					X													X					X		
Zandieh and Adibi 2008				X			X	X							X		X				X				X		X	X	X	X	X				X									X							X		
Zandieh and Gholami 2009			X				X								X		X				X				X	X					X		X																	X	X		
Zhang et al. 2012				X		X							X							X					X			X	X	X	X			X								X									X		
Zhang et al. 2013a				X			X	X							X		X				X	X			X			X	X	X	X		X				X			X									X			X	
Zhang et al. 2013a				X			X	X							X		X				X	X			X			X			X			X	X					X									X			X	
Zhang and Wu 2011				X		X							X							X					X			X	X	X	X			X									X								X		
Zhao et al. 2012				X			X	X				X			X		X				X				X	X		X			X		X																	X	X		
Zheng et al. 2012				X		X								X						X					X			X	X	X	X		X			X				X											X		

Figure 10: Overview and classification of all examined papers.