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Invited Review

Production, maintenance and resource scheduling: A review

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Production scheduling that involves maintenance activities and resource constraints plays a crucial role in manufacturing and service environments of the modern age. While research on the combination of production-maintenance scheduling and production-resource scheduling is constantly increasing, limited research is available on the integration of all three aforementioned scheduling problems. To unite both research directions, this paper provides a detailed review on both the integration of maintenance and resource with production as well as a review on all three scheduling problems together. This paper is the first survey paper to provide an extensive review on the combinations of production, maintenance and resource scheduling of approximately 250 papers that have appeared until the end of 2020. We not only provide a concise summary of the conducted research, but also offer recommendations for future research directions guided by practical importance.

1. Introduction

Timely and cost effective production is increasingly important in today's global competitive markets. This necessitates the joint efforts of many players to deliver effective strategies for supply management, planning and equipment/workforce scheduling. The players that are the main subject of this survey are manufacturers.

For manufacturers it is crucial to optimize equipment utilization by ensuring efficient schedules at the operational level. The majority of production scheduling problems assume that machines are continuously available. However, in many realistic situations, machines become unavailable for different reasons, such as unexpected breakdowns and maintenance. Despite the clear interdependency, production and maintenance scheduling are typically considered separately, both in industry and academia. Furthermore, in production scheduling studies, the only assets considered are the machines. Additional resources, such as tools or a specialized workforce, are frequently required in practice and need to be considered explicitly when making scheduling decisions. Therefore, in order to create an efficient production schedule, there is a need to take both scheduling of maintenance activities and resources into account.

The joint optimization of production scheduling and maintenance activities has attracted significant research interest over the past decades. This is also true for production scheduling with consideration of additional resources. However, the number of studies that consider both maintenance activities and additional resources is still limited. Literature surveys that address the integration of maintenance and production scheduling are provided by: Hadidi, Al-Turki, & Rahim (2012), Gordon, Strusevich, & Dolgui (2012), Li (2015) and Assia, Ikram, Abdellah, & Ahmed (2018). Hadidi et al. (2012) reviews the literature on the combination of maintenance, production and quality. Gordon et al. (2012) provides a brief review on scheduling maintenance activities with a main focus on the assignment of realistic due dates. Li (2015) summarizes the scheduling research that also takes maintenance into consideration. Assia et al. (2018) provides a comprehensive overview of integrated maintenance and production scheduling literature for flow shop environments. A survey on the integration of production scheduling and resources is conducted by Edis, Oguz, & Ozkarahan (2013).

Currently two largely separate research streams exist; one focuses on the integration of production and maintenance scheduling and the other is on production scheduling with the consideration of additional resources. In practical settings, maintenance scheduling and the need for additional resources are both intertwined with production scheduling. Bad alignment between the production and maintenance department may lead to disorganized use of resources, inefficient scheduling and unnecessary idle time on the

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machines. Motivated by the potential practical benefits, research that considers both maintenance scheduling and resource planning has recently started to emerge. This paper provides a thorough review of both streams of research separately and attempts to serve as an additional motive to bend both streams together.

As the surveys mentioned earlier show, at this moment, there is no study that explicitly reviews the integrated problem of scheduling production, maintenance and resources. Moreover, all of the surveys have some limitations. Li (2015) and Assia et al. (2018) discuss a small number of studies only, omit certain maintenance constraints and do not provide a structured classification. Hadidi et al. (2012) specifically focus on scheduling with auxiliary constraints such as quality and inventory control, thereby not providing an extensive review on maintenance and production scheduling. The review by Gordon et al. (2012) is also limited as it concentrates on studies with due date assignment only. Edis et al. (2013) provide a good review on production and resource scheduling, but only consider parallel machines. In this review, instead, we do not apply major restrictions and aim to provide a general review on three scheduling aspects: production, maintenance and resources. This is achieved by providing a separate review for each combination: production-maintenance, production-resources and production-maintenance-resources. In addition, a structured classification is presented and discussions with a specific focus on practical relevance are given. Research on integrated production, maintenance and resource scheduling is still in its early stage. It is therefor important to now review the work in this field in order to describe the opportunities and lay out directions for future research.

Given the large bodies of research, it is necessary to apply two constraints. Only deterministic problems are considered, i.e., studies that incorporate stochastic characteristics such as random breakdowns or corrective maintenance activities are excluded. Furthermore, only research that focuses on machine environments with more than one machine are included, i.e., all single machine environments are excluded as these are regarded of lesser practical relevance.

The remainder of this paper is organized as follows: definitions, notations, classifications and assumptions are provided in Section 2. Section 3 reviews the research that considers production scheduling with additional resources. Section 4 covers the literature on joint production and maintenance scheduling problems. Research that studies the integrated production and maintenance scheduling problem subject to additional resource constraints is reviewed in Section 5. Finally, concluding remarks are made in Section 6.

2. Definitions, notations, classifications and assumptions

This section describes several definitions, classifications and assumptions used throughout this survey. First, the general notation is introduced. Then, a more detailed classification on scheduling with maintenance activities and resources is given, as there are multiple sub-categories within these literature streams.

2.1. General

This survey adopts the three field notation $\alpha|\beta|\gamma$ by Graham, Lawler, Lenstra, & Kan (1979) to classify all papers. In this notation

- α represents the machine environment,
- β denotes job characteristics and problem constraints, and
- γ denotes the objective function.

Table 1 details the descriptions within each of the three fields. The first field, α, describes the shop or machine environment. For example, J, represents a job shop, where a number of jobs n needs to be processed on a set of m machines. Each job contains a set of operations O which needs to be processed in a specific order (precedence relations). Each of these operations can only be processed on a single machine. For further information regarding the other machine environments, we refer to Pinedo (2008).

β describes the job characteristics and constraints of the scheduling problem. This could be the information on maintenance activities, resources, shop conditions or details regarding the processing of a job. This field may contain multiple entries. For example, if $\beta = Prec, r_j, ST_{sd}$, then precedence relations, non-zero release dates and sequence dependent setup times are considered. The explanation of the specific notion used within the maintenance and resources literature streams are described in more detail in Sections 2.3 and 2.2, respectively.

γ field describes the objective function(s). Similar to the β field, it may have multiple entries. If more that one objective function is considered separately for the same problem, then the objective functions are separated by commas. For example, $\gamma = C_{\max}, \sum C_j$ means that the minimization of the makespan and the sum of completion times are considered. If multiple objective functions, each denoted by f_n are considered simultaneously, then it is denoted as $\gamma = z(f_1, f_2, \dots, f_n)$. Furthermore, if more than four objectives are considered, then $\gamma = \mathcal{F}$. If no objective function is given, then $\gamma = \emptyset$.

2.2. Classification of the resource literature

This section details the classification and notation within the resource literature. Depending on their renewability and divisibility, resources can be classified into two main categories according to Błażewicz, Ecker, Pesch, Schmidt, & Węglarz (2001). The first category related to the renewability of resources can be classified as follows:

- *Renewable*: availability of resources is constrained during usage. After processing a job, the resource becomes available again.
- *Non-Renewable*: consumption of resources is constrained. When the resource is used during the processing of a job, the resource does not become available again for any other job.
- *Double Constrained:* a resource is both constrained on its usage and consumption.

The second category related to the divisibility of the resource contains two sub-categories; *continuous* or *discrete* divisibility. In the former, the resource can be divided into any arbitrary number of parts, while in the latter the resource can only be divided into a finite set of possible parts.

Multiple types of resources are needed for executing scheduled manufacturing plans. The first, and the most common one, is workforce. Workforce is used in many different activities throughout production, such as; operating machines, transporting products, performing setups and conducting maintenance. Workforce is therefore the most versatile resource that can be considered within scheduling. Job scheduling with workforce consideration is referred to as the Dual Resource Constrained (DRC) problem, with resources being machines and workers. In the DRC problem, all resources are simultaneously required to process a job. Due to the versatility of the workforce, the DRC problem is also often more complex compared to other resources. Rules regarding the appointed time and location of the work force need to be taken into account. In addition, other special human characteristics may be considered. These are mostly related to learning and forgetting. These may influence processing times and, as a consequence, the efficiency of the shop floor. Therefore, multiple questions considering the workforce size and the required skills arise.

Many other types of resources are studied including pallets, fixtures, energy, tooling and transportation. In this review, only re-

Table 1
Description of α, β, γ fields.

α		β		γ	
Notation	Description	Notation	Description	Notation	Description
P	Parallel machines (identical)	$Prec$	Precedence constraints	$C_{\max}$	Makespan
Q	Parallel machines (uniform)	r_j	Non-zero release date	$E_{\max}$	Maximum earliness
R	Parallel machines (unrelated)	d_j	Non-infinite due date	$L_{\max}$	Maximum lateness
DR	Distributed Parallel machines (unrelated)	r	Resumable (preemption)	$T_{\max}$	Maximum tardiness
Fm	m-stage flowshop	nr	Nonresumable (preemption)	$D_{\max}$	Maximum Delivery time
FFm	m-stage flexible flowshop	sr	Semiresumable (preemption)	$\sum C_j$	Total completion time
HFm	m-stage hybrid flowshop	$no-wait$	No waiting time between 2 machines	$\sum F_j$	Total flowtime
AFm	m-stage assembly flowshop	$nmit$	No machine idle time	$\sum E_j$	Total earliness
J	Job shop	ST_{sd}	Sequence-dependent setup time	$\sum T_j$	Total tardiness
FJ	Flexible job shop	p_j	Processing time of a job	$\sum W_j$	Total waiting time
O	Open shop	LR	Learning effect	$\sum U_j$	Number of tardy (late) jobs
FMS	Distributed flexible manufacturing system	$h_{(win-flex-mn)}$	Non-availability window, flexible, m activities on n machines	$\sum w_jC_j$	Total weighted completion time
		$h_{(age-flex-mn)}$	Non-availability window before reaching the machine age	$\sum w_jF_j$	Total weighted flowtime
		$h_{(pos-flex-mn)}$	Non-availability window after producing a fixed number of jobs	$\sum w_jE_j$	Total weighted earliness
		$h_{(age-job-flex-mn)}$	Non-availability before reaching the machine age, job-specific deterioration	$\sum w_jT_j$	Total weighted tardiness
		$h_{(age-win-flex-m)}$	Non-availability where the time between two consecutive PMs is within an interval	$\sum w_jW_j$	Total weighted waiting time
		p_{int}	Interval processing times	$\sum w_jU_j$	Weighted number of tardy jobs
		$RMA_{m-time-mn}$	Rate-modifying activity, time-dependent maintenance duration deterioration	$\sum \theta_j u_j$	Cost of the # of assigned resources u to job j
		$RMA_{j-time-mn}$	Rate-modifying activity, time-dependent job duration deterioration	$W_{\max}$	Maximum machine workload
		$RMA_{m-pos-mn}$	Rate-modifying activity, position-dependent maintenance duration deterioration	$\sum Wm_j$	Total machine workload
		$RMA_{j-pos-mn}$	Rate-modifying activity, position-dependent job duration deterioration	$\sum CM_m$	Total Maintenance Cost
		$RMA_{m-job-mn}$	Rate-modifying activity, job-dependent job duration deterioration	$\sum TC_j$	Total tardiness cost jobs
		$RMA_{j-job-mn}$	Rate-modifying activity, job-dependent maintenance duration deterioration	$\sum TC_m$	Total tardiness cost maintenance
		IM	Imperfect maintenance	$\sum EC_j$	Total earliness cost jobs
		CP	Controllable processing times	$\sum EC_m$	Total earliness cost maintenance
		M_j	Set of eligible machines	$\sum CT_j$	Total cost
		$FR_{Weibull}$	Time to failure for a machine modeled by a Weibull distribution	$\sum TE_j$	Total energy consumption
		FR_{Exp}	Time to failure for a machine modeled by a Exponential distribution	$\sum TADC_j$	Total absolute deviation of job completion times
		$FR_{poisson}$	Time to failure for a machine modeled by a Poisson distribution	$\sum TADW_j$	Total absolute deviation of job waiting times
		res $\alpha\sigma\delta$	Resource characteristics	var_{TT}	Total tardiness variance
		LFL	Learn-Forget-Learn	$\mathcal{F}$	Multiple objective functions
		$LDRA$	Learning-Deteriorating Resource Allocation	$Avb_{\max}$	Maximizing machine availability
		s_j	Starting time		
		f_j	Finishing time		
		$Avb_{\max}$	Maximizing machine availability for determining optimal PM intervals		
		$Rlb_{\min}$	Maintaining a minimum reliability threshold		

sources that are required during job processing and maintenance activities are considered. Studies on AGV scheduling and on the Tool Switching Problem are out of scope. For the interested readers, surveys on these scheduling problems are provided by Ling, Wen-Jing, Qiu, Hsu, & Jing (1999), Vivaldini, Rocha, Becker, & Moreira (2015) and Calmels (2019).

We use the classification schemes proposed in Blazewicz, Lenstra, & Kan (1983), Kellerer & Strusevich (2008) and Edis et al. (2013). The β field is further detailed as $\beta \in \{\emptyset, res\lambda\sigma\delta\}$. Here λ, σ and δ are defined as:

- λ: number of resource types. If not specified, then $\lambda = \cdot$.
- σ: resource size. Resources are arbitrary if $\sigma = \cdot$.
- δ: upper bound for the resource requirements. No upper bound is specified if $\delta = \cdot$.

Furthermore, if resources influence processing times, the following additional terms can be added to the classification scheme:

- 'Bi': binary resource processing time. If job i receives an additional resource during processing, its processing time becomes $p_i - \pi_i$, otherwise it is p_i.

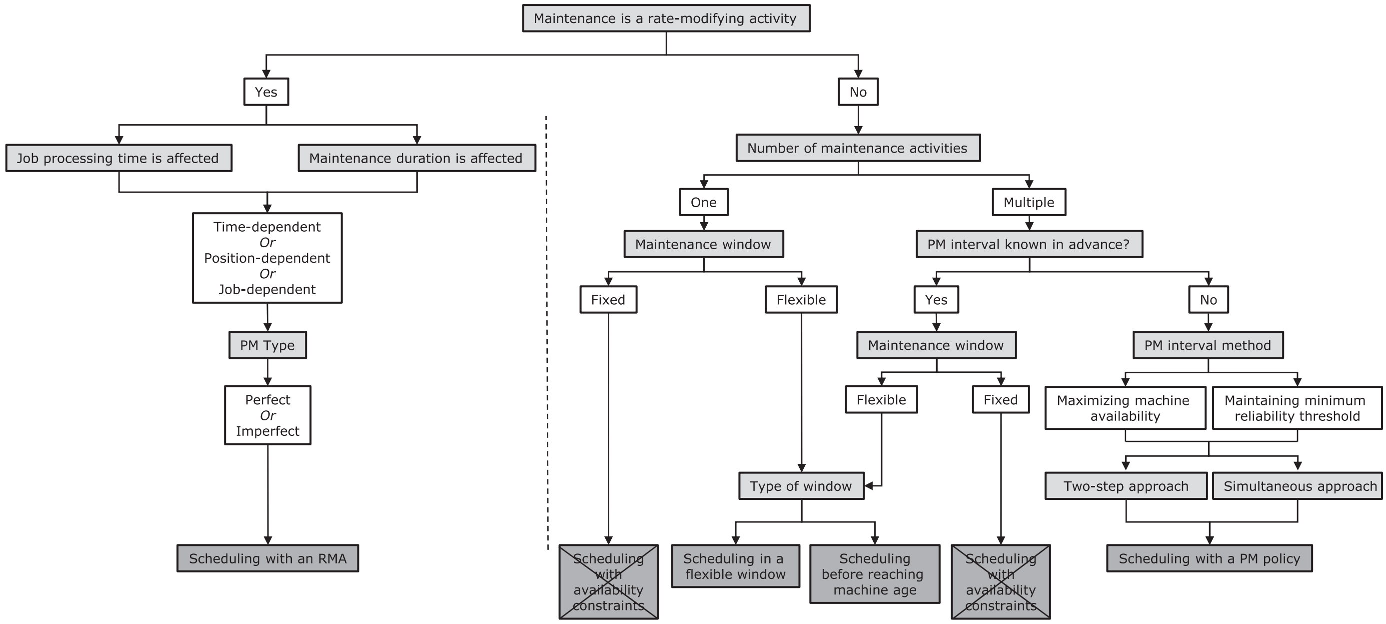

Fig. 1. Characteristics of the problem types for deterministic maintenance scheduling.

- 'Int': integer resource processing time. If job i receives additional resources of size τ, then its processing time becomes $p_{i\tau}$, otherwise it is p_i
- 'Lin': linear resource processing time. If job i receives an additional resource of size τ, its processing time linearly decreases with respect to τ, i.e., the processing time becomes $p_i - \tau \cdot \pi_i$, otherwise it is p_i

The papers considering resource constraints are classified into two different categories throughout this survey: (1) resources that influence the processing time, specifically, reducing the processing time (speed-up resource) and (2) resource requirements of jobs that are fixed and known (fixed resources). There are two subclasses within both categories: static and dynamic allocation of resources. In the former, the resource cannot switch to different machines, while in the latter such switches are allowed.

2.3. Classification of the maintenance literature

In this section, the notations that are used within scheduling with maintenance activities are described in more detail. Deterministic maintenance scheduling problems can be classified according to several characteristics. A schematic overview is given in Fig. 1. A clear distinction can be made in terms of maintenance activity type. The first type considers research where the maintenance activity may change the machine speed or the maintenance duration may increase over time. This is called scheduling with a rate-modifying activity (RMA), as deterioration takes place on the machines. Lee & Leon (2001) are the first to study this class of scheduling. The three most frequently used deterioration effects are:

- *Time-dependent deterioration*: $p_i = p_i + a_j t_{ik}$ where p_i is the normal processing time of job i, $a_j > 0$ is the common deterioration factor on machine M_j and t_{ik} is the starting time of a job processed on the position k of machine M_j.
- *Position-dependent deterioration*: $p_i = p_i + a_j k$ where p_i is the normal processing time of job i, k is the kth position in the sequence and $a_j > 0$ is the common deterioration factor on machine M_j.
- *Job-dependent deterioration*: $p_i = p_i^{a_{ij}}$ where $p_i > 0$ is the normal processing time of job i and $a_{ij} > 0$ is the deterioration factor of job i on machine M_j.

Based on these three effects, multiple variations and combinations of deteriorating properties exist. For example, job-dependent deterioration can be combined with position-dependent deterioration, i.e., $p_i = p_i k^{a_{ij}}$. This study provides categorisation according to the three main deteriorating effects. When an RMA is performed, literature considers either the case where the machine is restored to a 'as good as new state' or to a 'less deteriorated state', which are called perfect Preventive Maintenance (PM) and imperfect PM, respectively.

When RMA is not performed, a maintenance activity must be scheduled according to a different set of constraints, related to flexible scheduling windows for maintenance and maintenance based on machine characteristics. First, a division is made between the number of maintenance activities. When only one maintenance activity is scheduled per machine, PM based on intervals is not possible. In this case, constraints related to maintenance apply on one activity only. Two types of settings are examined in this instance. One setting considers the case where the start and end of maintenance have to be within a time window and where the duration of maintenance is smaller than the duration of the time window. The other setting examines the case where a maintenance activity must be scheduled before the machine reaches a certain age, referred to as the Remaining Useful Life (RUL) of the machine. When the machine is restored, the next maintenance activity must again be scheduled before reaching the end of RUL. In case it is known exactly when maintenance is going to take place, jobs have to be scheduled along these windows of machine unavailability. In the literature, this is referred to 'scheduling with availability constraints'. Since maintenance cannot be scheduled in this category, it is not studied in this survey. We refer the interested readers to the following surveys on this category: Schmidt (2000) and Ma, Chu, & Zuo (2010).

For multiple maintenance activities, further classification depends on whether the PM interval is known in advance or not. When the PM interval is known in advance, the two settings described before are studied, as these settings also apply to the case of multiple maintenance activities. When PM is not known in advance, either a two-step approach or a simultaneous approach is considered. In the two-step approach, the first step is to determine the optimal interval between consecutive maintenance activities. The optimal interval depends on constraints regarding the availability and reliability of the machines. Two specific objectives are considered:

- *Maximizing machine availability*: the goal is to maximize machine availability by defining the interval between PM activities based on the reliability model of a system and on the failure and repair data of the machines. Availability may be considered for each machine separately or for all machines combined. Most studies consider a Weibull distribution for the inter failure times.
- *Maintaining a minimum reliability threshold*: it is assumed that the failure rate of a system is increasing over time and therefore it may be affected by failures due to aging or wear. The interval between PM activities is chosen such that a minimum reliability of the system is ensured throughout a scheduling horizon.

Once the PM intervals are determined, the second step is to schedule the production activities in combination with the PM activities. While scheduling maintenance and production activities simultaneously, the maintenance activities may deviate from their interval derived in the first step. In that case, dependent on the strategy that is used, the PM activities may be delayed or advanced.

In the simultaneous approach, the decision when to perform PM must be taken simultaneously with production scheduling. Though, it is still based on either the *Maximizing machine availability* objective or the *Maintaining a minimum reliability threshold* objective.

Scheduling with these objectives may be viewed as a combination of scheduling with a flexible window and scheduling before reaching the RUL. Since, there is no strict window to force the PM to be scheduled according to hard constraints. Yet, at the same time, a window is eventually created through one of the two objectives. Thus, it has more resemblance to scheduling before reaching the RUL, where a soft window is applied around the threshold of the RUL.

With regards to the notation for the maintenance scheduling problems, no classification exists yet to characterize scheduling problems with an RMA and scheduling in a flexible window. Therefore, this paper proposes a new notation to characterize these problems. The proposed notation is detailed in Table 1.

Studies that include a maintenance activity may consider preemption. In non-preemptive scheduling, a job cannot be interrupted by another process. With preemptive scheduling, three types of preemption exist:

- *Resumable*: the job can proceed without any additional cost or processing time once the interruption is finished.
- *Semi-resumable*: the job may proceed once the interruption is finished, but cost is incurred resulting in an increased processing time.
- *Non-resumable*: the job has to completely restart after the interruption is finished, i.e., the remaining processing time of the job is set to its original processing time.

As a summary, four main categories are used to describe the maintenance scheduling literature. These categories are: 'Scheduling with an RMA', 'Scheduling in a flexible window', 'Scheduling before reaching machine age' and 'Scheduling with a PM policy'. The first category comprises literature that deals with an RMA. The second category includes research where the interval is known in advance and PM may be scheduled flexibly in a time-window. The third category contains literature where the interval is known in advance and maintenance must be scheduled before reaching a certain age. The last category involves research where scheduling PM is performed according to a specific objective related to the availability or reliability of the machines.

In the next sections, the results for scheduling with resources or maintenance activities are presented. Within these sections, three machine environments are considered; (i) (Flexible) Job Shops and Open Shops, (ii) Parallel Machines and (iii) Flow Shops. For each machine environment, a detailed review of the available literature is provided. In addition, the main findings and further research possibilities and needs are discussed by answering the following research questions:

1. What are the contributions of the covered research papers to the literature? What novelties are introduced?
2. What is missing in the covered research field? This is analyzed from two angels: (1) the type of problems, solution methods, objective functions or used data set and (2) the comparison and benchmarking performed for the studies within the related field.
3. What are the opportunities? What research that is both important and lacking can be addressed?

Sections 3 and 4 end with the take-aways and summarize the main findings. In Section 5 an overview of scheduling considering both resources and maintenance activities is provided. Within this section, no division is made between machine environments. A list of abbreviations that are used in the subsequent sections is provided in Table 2.

3. Resources

3.1. (Flexible) job shop and open shop

This section considers a job/open shop environment, for both fixed and speeding up resource types. An overview of the literature is given in Table 3.

3.1.1. Scheduling with fixed resource types

Elvers & Treleven (1985) study the effect of routing patterns within DRC shops, i.e., a pure job shop, a flow shop or a mixture of the two. The authors make use of several dispatching rules, such as First-Come-First-Serve (FCFS) and Earliest Due Date. They test the effect these rules have on performance measures related to tardiness and queue statistics. Three different job-routing-patterns are evaluated, related to the number of jobs that have either a job shop or flow shop routing. The studies conclude that (1) the routing patterns have no significant influence on the chosen dispatching rule and (2) insights for pure job shop environments may also be used in flow shop environments. Bobrowski & Park (1989) on the other hand, investigate the effects of order release rules on the performance of DRC shops. Four different rules are tested of which the mechanisms Forward Finite Loading and Backward Infinite Loading prove to work best due to their ability to use shop information.

Patel, ElMaraghy, & Ben-Abdallah (1999) propose Genetic Algorithms (GA) to solve the DRC shop problem. The shop contains a heterogeneous work force and the performance of the proposed solution method is tested on eight different performance measures. In addition, six different job dispatching rules are tested, both on the DRC shop and on a shop with only machines being the limiting resource. The authors conclude that (1) the best dispatching rule depends on the chosen performance measure and (2) the best dispatching rule in a machine limited environment does not have to be the best in a DRC environment. The authors continue their work in Elmaraghy, Patel, & Abdallah (2000) and show that

Table 2
List of Abbreviations.

ACO	Ant Colony Optimization	*FFO*	Fruit Fly Optimization	*MOMA*	Multi Objective Memetic Algorithm
GA	Genetic Algorithm	*FJSP*	Flexible Job Shop Problem	*NEH*	Nawaz-Enscore-Ham
ABC	Artificial Bee Colony	*FPTAS*	Fully Polynominal Time Approximation Scheme	*NPM*	Nested Partitions Method
AIS	Artificial Immune System	*GA*	Genetic Algorithm	*NRGA*	Non-Ranking Genetic Algorithm
B&B	Branch and Bound	*GRASP*	Greedy Randomized Adaptive Search Procedure	*NSGA*	Non-Sorting Genetic Algorithm
BPGA	Branch Population Genetic Algorithm	*HFSA*	Hybrid Firefly Simulated Annealing	*PM*	Preventive Maintenance
CP	Constraint Programming	*HS*	Harmony Search	*PSO*	Particle Swam Optimization
CPSO	Chaotic Particle Swarm Optimization	*ICA*	Imperialist Competitive Algorithm	*PTAS*	Polynomial-Time Approximation Scheme
DABC	Discrete Artificial Bee Colony	*IP*	Integer Program	*RMA*	Rate-Modifying Activity
DP	Dynamic Programming	*ILP*	Integer Linear Program	*RPD*	Relative Percentage Deviation
DNS	Dynamic Neighbourhood Search	*LP*	Linear Program	*RUL*	Remaining Useful Life
DRC	Dual Resource Constrained	*LPT*	Longest Processing Time	*SA*	Simulated Annealing
DRCJSP	Dual Resource Constrained Job Shop Problem	*MA*	Memtic Algorithm	*SPT*	Shortest Processing Time
DRCFJSP	Dual Resource Constrained Flexible Job Shop Problem	*MILP*	Mixed Integer Linear Program	*TS*	Tabu Search
DRCO	Discrete Chemical-Reaction Optimization	*ML*	Maintenance Level	*VDO*	Vibrating Damping Optimization
FBS	Filtered Beam Search	*MO*	Multi Objective	*VNS*	Variable Neighbourhood Search

Table 3
Job/Open shop scheduling with resources.

Resource Effect	References	$\alpha\|\beta\|\gamma$ Notation	Approach
Fixed	Elvers & Treleven (1985)	$J\|res\cdot\cdot\|\mathcal{F}$	Dispatching Rules
	Bobrowski & Park (1989)	$J\|res\cdot\cdot1\|\mathcal{F}$	Order Release Rules
	Patel et al. (1999)	$J\|res\cdot\cdot1\|\mathcal{F}$	GA, Dispatching Rules
	Elmaraghy et al. (2000)	$J\|res\cdot\cdot1\|\mathcal{F}$	GA
	Araz (2005)	$J\|res\cdot\cdot1\|\mathcal{F}$	Artificial Neural Network
	Araz (2007)	$J\|res\cdot\cdot1\|\mathcal{F}$	Artificial Neural Network
	Araz & Salum (2010)	$J\|res\cdot\cdot1\|\mathcal{F}$	Artificial Neural Network
	Zhang et al. (2017)	$J\|res\cdot\cdot1, S_j\|C_{\max}$	Hybrid Discrete PSO
Speeding Up	Huang et al. (1984)	$J\|res\cdot\cdot1\|\mathcal{F}$	Dispatching Rules and Labor Assignment
	Treleven & Elvers (1985)	$J\|res\cdot\cdot1\|\mathcal{F}$	Labor Assignment
	Park & Bobrowski (1989)	$J\|res\cdot\cdot1\|\mathcal{F}$	Job Release, Labor Flexibility, Job Dispatching
	Park (1991)	$J\|res\cdot\cdot1\|\mathcal{F}$	Labor Flexibility, Dispatching Rules
	Felan et al. (1993)	$J\|res\cdot\cdot1\|\mathcal{F}$	Labor Flexibility, Labor Size
	Malhotra et al. (1993)	$J\|res\cdot\cdot1, LFL\|\mathcal{F}$	Labor Flexibility, Learn-Forget-Learn
	Fry et al. (1995)	$J\|res\cdot\cdot1, LFL\|\mathcal{F}$	Labor Flexibility, Learn-Forget-Learn
	Kher & Malhotra (1994)	$J\|res\cdot\cdot1\|\mathcal{F}$	Labor Flexibility
	Malhotra & Kher (1994)	$J\|res\cdot\cdot1\|\mathcal{F}$	Worker Transfer Rules
	Renna et al. (2020)	$FJ\|res\cdot\cdot1\|\mathcal{F}$	Worker Transfer Rules and Game Theory
	Kher et al. (1999)	$J\|res\cdot\cdot1, LFL\|\mathcal{F}$	Learn-Forget-Learn
	Kher (2000)	$C\|res\cdot\cdot1, LFL\|\mathcal{F}$	Learn-Forget-Learn
	Jensen (2000)	$C\|res\cdot\cdot1, LFL\|\mathcal{F}$	Staffing Levels
	Kher & Fry (2001)	$J\|res\cdot\cdot1\|\mathcal{F}$	Labor Flexibility, Assignment Policies, Order Dispatching
	Felan & Fry (2001)	$J\|res\cdot\cdot1\|\mathcal{F}$	Labor Flexibility
	Yue et al. (2008)	$J\|res\cdot\cdot1, LFL\|\mathcal{F}$	Labor Flexibility, Learn-Forget-Learn
	Bokhorst et al. (2004)	$J\|res\cdot\cdot1\|\mathcal{F}$	'Who'-rule
	Kannan & Jensen (2004)	$C\|res\cdot\cdot1, LFL\|\mathcal{F}$	Labor Flexibility, Assignment Policies, Order Dispatching
	Salum & Araz (2009)	$FMS\|res\cdot\cdot1, LFL\|\mathcal{F}$	Worker Transfer Rules
	Jaber & Neumann (2010)	$FMS\|res\cdot\cdot1\|\mathcal{F}$	Worker Fatigue and Recovery
	Li et al. (2010a)	$J\|res\cdot\cdot1, Bi, S_j\|\min\max f_i$	ACO
	Li et al. (2010b)	$J\|res\cdot\cdot1, Bi\|TC$	ACO
	Li et al. (2011)	$J\|res\cdot\cdot1, Bi, S_j\|TC$	ACO and SA
	Lei & Guo (2014)	$FJ\|res\cdot\cdot1, Bi\|C_{\max}$	VNS
	Deming Lei & Guo (2014)	$J\|res\cdot\cdot1, Bi\|z(C_{\max}, TCE)$	DNS
	Zheng & Sui (2019)	$J\|res\cdot\cdot1, Bi, S_j\|z(C_{\max}, TEC)$	Epsilon Method, NSGA
	Meng et al. (2019)	$FJ\|res\cdot\cdot1, Bi, S_j, f_i\|z(C_{\max}, TE)$	VNS
	Zhu et al. (2020)	$FJ\|res\cdot\cdot1, Bi, Learn\|z(C_{\max}, TE)$	MA
	Yazdani et al. (2015)	$FJ\|res\cdot\cdot1, Bi\|C_{\max}$	SA,VDO
	Li et al. (2016)	$J\|res\cdot\cdot1, Bi, S_j, f_i\|z(C_{\max}, TC)$	Branch Population GA
	Zhong & Yang (2018)	$J\|res\cdot\cdot1, Bi\|z(C_{\max}, TC)$	Branch Population GA
	Zheng & Wang (2016b)	$FJ\|res\cdot\cdot1, Bi\|C_{\max}$	FFO
	Paksi & Ma'ruf (2016)	$FJ\|res\cdot\cdot1, Bi\|T_{\max}$	GA
	Wu et al. (2018)	$FJ\|res\cdot\cdot1, Bi, Learn\|C_{\max}$	Hybrid GA
	Yazdani et al. (2019)	$FJ\|res\cdot\cdot1, Bi\|z(C_{\max}, TWM, CMW)$	GA
	Yang et al. (2019)	$FJ\|res\cdot\cdot1, B, DD_i i\|z(C_{\max}, L_{\max}, TADC)$	Limited Search Space-Based Algorithm
	Andrade-Pineda et al. (2020)	$J\|res\cdot\cdot1\|z(C_{\max}, \tau\cdot\sum_{i=1}^{m}\frac{t_{v_i}}{m})$	Greedy Algorithms

for a given performance measure and dispatching rule, their proposed GA provides the best schedule. Instead of only choosing a single dispatching rule to schedule jobs, Araz (2005) develops a multi-criteria scheduler that selects the best dispatching rule based on previous shop floor performance, and on the situation at the time of dispatching. They develop Artificial Neural Networks (ANN) to solve the problem. The scheduler chooses the best dispatching rule based on the best cost function. Continuing their work, Araz (2007) replaces the previously proposed Multi Criteria Decision Aid with a fuzzy system interface. The fuzzy interface provides aggregated performance measures for each shop configuration and selects the best one. Further, in Araz & Salum (2010), the authors also make the worker assignment rules dynamic (i.e., the 'when' and 'where' rules). In addition, the authors investigate how often the model should be updated and state that the chosen scheduling length depends on the system status. Later, Zhang, Wang, & Xu (2017) study the DRC flexible job shop problem under the assumption of homogeneous workers. The authors propose a Hybrid Discrete Particle Swarm Optimization (PSO) algorithm to solve the scheduling problem. The algorithm consists of three phases, initialization of the population, global search through a discrete PSO and a local search through Variable Neighbourhood Search (VNS) and Simulated Annealing (SA). Compared to other heuristics such as GA, the proposed method is more effective in finding good solutions.

3.1.2. Scheduling with speeding-up resource types

Huang, Moore, & Russell (1984) study the effects of four dispatching rules (e.g., FCFS and Shorted Processing Time) and three labor assignment rules in a DRC job shop under different workload conditions. The Shortest Processing Time (SPT) rule proved to be the best performer for all utilization rates. However, the difference with other rules is only significant when the utilization rate is high. Furthermore, the job assignment rules seem to have no significant effect on the shop performance, compared to job sequencing rules. Similarly, Treleven & Elvers (1985) also study the effect of labor assignment rules. In their work, 11 different rules are evaluated on multiple shop environment types. These rules are based on combinations of labor assignment rules and dispatching rules. Their conclusion is that labor assignment rules seem to have no significant impact on the performance of the shop. Park & Bobrowski (1989) investigate the effect of job release mechanisms along with five combinations of labor flexibility and degree of work cross training, on nine different performance measures. Their main conclusion is that the order release mechanism, constituting of Forward Finite Loading and Backwards Infinite Loading, seems to have no effect on total cost performance. Furthermore, worker flexibility has a significant effect on the shop performance, but only when the increase is minimal, from no flexibility to one additional machine. They show that any further increase has close to no effect. Their work is extended in Park (1991), which evaluates besides worker flexibility, five different dispatching rules. The study concludes that the performance of dispatching rules stays the same across different flexibility levels. Felan, Fry, & Philipoom (1993) investigate the effects of worker flexibility and compare the results against an increase in labor force. Both options increase the performance of the shop. However, an increase in labor force has a more pronounced effect on performance measures, yet at a higher cost. The authors conclude that a combination of both options is the best choice.

Malhotra, Fry, Kher, & Donohue (1993) study a different effect of workers, specifically related to learning effects. They arrive at the same conclusion on worker flexibility as Park & Bobrowski (1989), which is that worker flexibility only has a significant effect when the increase is minimal. Notably, they also confirm this under extreme conditions, when worker learning rates are low and attrition is high. Though, the authors also conclude that increasing labor flexibility comes at a cost of a decrease in labor efficiency, especially when the learning rates are low. Fry, Kher, & Malhotra (1995) conclude the same and also state that companies should consider decreasing labor attrition, since managing inventory levels and due date adherence give a less dramatic improvement. Nevertheless, decreasing labor attrition leads to a decreased labor variability. Similar conclusions regarding worker learning are given by Kher & Malhotra (1994), Kher, Malhotra, Philipoom, & Fry (1999), Kher (2000), Jaber & Neumann (2010) and Kannan & Jensen (2004). Kher et al. (1999) also consider the learn-forget-learn model. Within this model, different forgetting and learning rates are applied and the authors examine this on the final efficiency of the workers. The authors conclude that decreasing a workers forgetting rate is more beneficial than increasing flexibility. Their work is extended in Kher (2000), which indicates that the benefits of worker flexibility depends on the situation. Jaber & Neumann (2010) also study worker fatigue (and recovery), which may decrease the performance of workers. In order to analyze the effects, the authors formulate a Mixed Integer Linear Programming (MILP) model to solve the problem and answer research questions related to worker fatigue. Their main findings state that introducing short breaks, short cycle times and increased recovery rates help to increase the performance of the system. Kannan & Jensen (2004) examine cellular manufacturing shops, which are sometimes more effective than traditional job shops. The authors consider learning effects, staffing levels and multiple labor assignment rules. They arrive at similar conclusions within this environment as the previous studies.

Kher & Malhotra (1994) also test rules related to time of transfer of a worker and where the worker should be transferred to. They conclude that the former rule is of more importance, and show that the rule indicating when workers are eligible for transfer after each job (the centralized 'when' rule) performs best. Malhotra & Kher (1994) also study the effect of these rules in a similar environment. The overall conclusion, for all shops, is to let workers operate in the department where they are most efficient, until all work at that department is exhausted. More recently, Renna, Thürer, & Stevenson (2020) consider the same problem, using game theory as an approach to solve the worker assignment problem. They show an increased performance compared to more traditional 'when' and 'where' rules. Salum & Araz (2009) consider a hybrid push/pull system in a DRC job shop. Workers in this shop are responsible for both transportation and processing of parts. 'When', 'where', 'process-or-transport' and 'where-to' rules are all used in the simulation model. The main conclusion is that 'where' rules seem to have no significant effect on the performance measures, which is in line with all previous studies. Bokhorst, Slomp, & Gaalman (2004) study the 'who' rule. This rule is used to decide which worker to transfer to a certain workcenter, but only in the case where more than one skilled worker is available. The 'who' rule depends on the characteristics of the chosen shop. Shops with a lower utilization typically benefit more from using the 'who' rule. This is also the case when worker flexibility is based on the proficiency of workers, instead of the skillset of workers.

Jensen (2000) study the effect of staffing levels on the performance of the shop floor, with the addition of also considering different shop floor layouts. The authors mainly consider cellular layouts for the shop floor. The most important conclusion is that strict cellular layouts, in comparison to hybrid layouts, provide the best flowtime and tardiness when staffing levels are low to moderate. Continuing in the field of labor flexibility, Kher & Fry (2001) investigate labor flexibility, assignment policies, order dispatching rules and priority customers. In particular, they study their effect on the performance of the shop floor, while looking at on time delivery. They conclude that it is more effective to increase labor flexibility, as this also benefits priority customers, but not at the cost of other customers. Felan & Fry (2001) consider the same problem and conclude that a lower level of flexibility may perform as good as a level where all workers are trained evenly. Shop performance may also increase when there is a mix of skilled workers, especially with some workers being highly trained but not all, which comes at a lower cost. Yue, Slomp, Molleman, & Van Der Zee (2008) also investigate the effect of worker flexibility, under learning and forgetting. The authors conclude that shop floor dynamics need to be taken into account while selecting cross training policies. This is due to the fact that the frequency of new part introduction can influence (1) the extent to which workers are cross trained, (2) the number of overlapping skills between workers and (3) how the skills are distributed between workers.

Li, Li, Liu, & Li (2010a) consider a DRC problem with heterogeneous workers. In order to solve the problem, the authors propose a hybrid algorithm that builds upon an Ant Colony Optimization (ACO) algorithm. The ACO proves to work well compared to other algorithms. The authors continue their work in Li, Sun, Huang, & Wang (2010b) and add self adapting parameters. These parameters influence the proposed heuristic, both in its ability to converge to an optimum solution and in expanding the search space. Parameters are adapted either linearly over time or based on whether a better solution is found. Results show better performance than the former method of Li et al. (2010a). Lastly, in Li, Sun, & Huang (2011) the authors add a local search method based on SA to avoid getting stuck in local optimums.

Lei & Guo (2014) propose a VNS method to solve the DRC flexible job shop problem, with the objective to minimize the makespan. Results are promising compared to other solutions in literature, such as GA. In later work, Deming Lei & Guo (2014) extend the research by also considering environmental objectives. A DRC interval job shop with heterogeneous workers is considered with the objective, besides minimizing the makespan, to reduce the total carbon footprint of a job shop (i.e., reduce energy consumption). To achieve this, the authors propose a Dynamic Neighbourhood Search (DNS) which consists of two phases. Compared to GA and VNS, the proposed method shows promising results. Zheng & Sui (2019) also consider the same problem with the objective to minimize energy consumption. The authors propose an exact epsilon constraint method and a Non-Sorting GA (NSGA) to solve the problem. The former method finds an optimal solution for small sized problems, while the latter is effective in finding solutions for large sized problems. Meng, Zhang, Zhang, & Ren (2019) also consider the objective of minimizing the total energy consumption. The authors propose a VNS with eight different neighbourhood structures to solve the problem. Results show that all methods provide effective solutions. Lastly, Zhu, Deng, Zhang, Hu, & Lin (2020) consider the same problem, with the addition of worker learning. The authors develop a Memetic Algorithm (MA) and prove that their solution method outperforms other multi-objective methods on benchmark cases.

Yazdani, Zandieh, Tavakkoli-Moghaddam, & Jolai (2015) also study the DRC flexible job shop problem. Similar to Lei & Guo (2014), they make use of neighbourhood structures to improve the solution space. The authors develop two meta-heuristics, one related to SA and the other based on Vibration Damping Optimization (VDO). Workers are considered to be heterogeneous, having different processing times on different machines. Various sized data sets are generated and results show that VDO heuristic outperforms SA. Further, Li, Huang, & Niu (2016) propose a meta-heuristic to solve a similar problem. Their proposed solution method is referred to as Branch Population GA (BPGA), which is a hybrid version of GA and a Branch Population Algorithm, used to transfer evolutionary experience from parent chromosomes to child chromosomes. Other techniques are also introduced to, for example, reduce computational time or improve scheduling. Compared to other algorithms from literature, results show that the proposed method is more effective. Similarly, Zhong & Yang (2018) propose a BPGA to solve the DRC Job Shop Problem (DRCJSP), based on a compressed time window scheduling strategy, under the objective of minimizing makespan and total costs. Compared to an NSGA algorithm of the same authors, BPGA provides better results, lowering both objectives.

Other meta-heuristic methods to solve the DRC Flexible Job Shop Problem (DRCFJSP) are, e.g., given by Zheng & Wang (2016b). The authors propose a knowledge-guided fruit fly optimization algorithm. Fruit fly Optimization (FFO) basically mimics the foraging behaviour of fruit flies (similar to the aforementioned ACO). The addition of a knowledge-guided search helps to improve the search results, using previously gained knowledge of resource assignments and operation sequences. Compared to an existing VNS by Lei & Guo (2014), the proposed method is more effective. Further, Paksi & Ma'ruf (2016) propose GA to solve the DRCFJSP with the objective to minimize tardiness. They evaluate their algorithm within a company and report a 26% improvement in tardiness. Wu, Li, Guo, & Xu (2018) consider the addition of learning effects, which are based on the accumulation of processing times. A hybrid GA is proposed which is shown to be effective in finding good quality solutions. Yazdani, Zandieh, & Tavakkoli-Moghaddam (2019) propose multiple evolutionary algorithms, based on GA, to solve the DRCFJSP under the objective of minimizing makespan, critical machine workload and total workload. Four algorithms are proposed, each with non dominated sorting or ranking procedures or elitism control. Compared to one another, each of the four proposed algorithms has an advantage, depending on the chosen performance measures. Yang, Chung, & Lee (2019) consider the problem under the influence of multi-level product structures. A method, called limited search space-based algorithm, is used to solve the stated problem, with the objective to minimize makespan, lateness and total workload. Compared to GA based algorithms, the proposed method is in most cases more effective in finding solutions for larger sized problems, but is outperformed by GA for smaller sized problems. Andrade-Pineda, Canca, Gonzalez-R, & Calle (2020) consider the DRCFJSP with the addition of taking dynamic events into account, such as rush jobs. This problem is common in an auto repair shop. The authors develop a method based on two alternative greedy algorithms, which solve the subproblems of machine scheduling and worker scheduling. Results show that the developed algorithms can solve the stated problems in a small amount of time, thus being useful when dynamic changes happen often and rescheduling is needed quickly.

3.1.3. Discussion

There is a substantial amount of research on resource scheduling in a job shop. However, the bulk of this literature considers speeding up resources, mostly related to labor. Regarding fixed resources, all studies consider similar problems regarding the types of resources used, with a slight variety in solution methods. Compared to other machine environments, such as parallel machines (which is featured in Section 3.2), research on job shop scheduling with fixed resources is lacking. This makes it difficult to asses the novelties in this field, as both the problem field and the solutions are not diverse enough. The majority of the studies have been carried out by Araz (2005), which have not received any follow up studies. However, this potentially has other causes. A significant number of resource scheduling problems have been considered separately from the job shop scheduling problem (e.g., the tool switching problem, transportation scheduling, material planning). This makes it difficult to compare existing literature, especially in the domain of fixed resources, as it is often not known what resources are exactly considered. Therefore, the term "resource scheduling" should be used more explicitly, in order to compare various problems and solution methods. Future work on the fixed resources category should also study more diverse solution approaches such as machine learning. A major opportunity would be to investigate the effects of resource types on different objectives, for example, minimizing the weighted tardiness of jobs.

Considering speeding up resources, most of the pioneering literature (e.g., the studies by Treleven & Elvers, 1985 and Fry et al., 1995), do not primarily focus on the scheduling aspect of the problem, but rather on the influence that labor has on scheduling. These papers have received a lot of follow up research, with most studies extending research performed by previous authors to better understand the influence of specialized labor resources. More recently however, a switch is noticed where studies focus more on application of heuristics, meta-heuristics and algorithms to solve the scheduling problem under influence of limited resources. There is a large variety in the studied solution approaches. However, these approaches are only occasionally compared against previous results by means of a benchmark. The most important opportunity in this field is to map the best solution methods through benchmarking. In addition, almost all studies consider binary resources. It would be interesting to the see the effect of both integer and linear resources within the job shop environment.

3.2. Parallel machines

This section considers a parallel machine environment, for both fixed and speeding up resource types. An overview of the literature for this section is given in Tables 4 and 5 for fixed and speeding up resource types, respectively.

3.2.1. Scheduling with fixed resource types

Solving the parallel machine scheduling problem under resource constraints is studied thoroughly in literature. Multiple authors prove that some of these problems can be solved in polynomial time. For example, Garey & Johnson (1975) investigate the problem of two parallel machines, where the processing time of jobs is equal to one and resource constraints are arbitrary. This problem is shown to be solvable in $O(m^3)$ time, where m is the number of machines. Other studies, such as Blazewicz (1979), Błażewicz, Kubiak, Röck, & Szwarcfiter (1987), Brucker & Krämer (1996), Ventura & Kim (2000), Ventura & Kim (2003) and Kellerer & Strusevich (2003b) also consider problems on parallel dedicated machines and prove that problems under different resource constraints can also be solved in polynomial time. In addition, Blazewicz et al. (1983) and Kovalyov & Shafransky (1998) prove that uniform parallel machines can also be solved in polynomial time. The exact problems and solution times of the aforementioned studies are shown in Table 4. In addition to the polynomial solvable problems given by Kellerer & Strusevich (2003b), the authors also develop algorithms for the aforementioned problems. Continuing their work, Kellerer & Strusevich (2003a) consider two extensions of their previous problem, where there are λ resource types. The authors develop a greedy algorithm for the dedicated machine problem and a Polynomial-time Approximation Scheme (PTAS) for the problem with m parallel machines.

In contrast to finding polynomial time approximation schemes, other authors aim to prove NP-Hardness of certain problems. For example, Blazewicz et al. (1983) examine the cases for identical parallel machines and uniform parallel machines, with a single resource and unit processing time. They prove that both are NP-Hard in the strong sense. The authors later continue their work in Błazewicz, Barcelo, Kubiak, & Röck (1986) and prove that two slightly different problems for identical parallel machines are also NP-Hard. More examples of studies that prove NP-hardness for similar problem types are shown in Błażewicz et al. (1987), Kellerer & Strusevich (2003b), Kellerer & Strusevich (2003a) and Kellerer (2008) and are summarized in Table 4.

Solving these NP-hard problems can be done through either exact approaches such as a Branch-and-Bound (B&B) method or, alternatively, approximations and heuristics, such as approximation algorithms and meta heuristics. Błażewicz et al. (2001) point out three reasons for NP-Hardness: (1) non-identical ready times of jobs, even under simple resources and low ($m = 2$) number of machines, (2) an increase from two to three machines and (3) the addition of precedence constraints. In order to solve these problems, either an approximation algorithm is needed or an exact approach can be used. Slowinski (1988) consider the problem of unrelated parallel machines where a machine and product combination requires at most one specific resource at any given time. The authors develop a two-phase method to solve the problem and conclude that the problem, by using the proposed algorithm, can be solved in polynomial time.

Błazewicz, Kubiak, & Martello (1993) consider the two machine problem. In order to solve this problem, the authors propose a B&B algorithm and two heuristic algorithms. Srivastav & Stangier (1997) consider a similar problem, taking start times into account. The authors provide a polynomial time algorithm within a factor of $1 + \epsilon$ by generalizing the problem as a multidimensional bin packing problem. Józefowska, Mika, Rózycki, Waligóra, & Weglarz (2002) study parallel identical machines with the addition of continuous renewable resources with the aim to minimize the makespan. The authors propose two heuristics integrated within Tabu Search (TS) to solve the problem. Ventura & Kim (2003) examine a problem with an arbitrary number of resource types and resource requirements per job, similar processing times for each job and distinct ready time and due dates. To solve this problem, the authors first formulate the problem as a 0–1 Integer Linear Program (ILP) and use Lagrangian relaxation as solution procedure. Results show that near optimal results can be achieved through this method, also for larger sized problems.

Edis, Araz, & Ozkarahan (2008), Edis & Ozkarahan (2011), Edis & Ozkarahan (2012), Edis & Oguz (2011) study the problem of unrelated parallel machines with a single resource, an upper bound of two on resource availability and unit processing time, with the exception of Edis & Oguz (2011), which considers uniform parallel machines and Edis & Ozkarahan (2011), that considers deterministic task times. However, all studies use similar solution methods, typically Integer Programming (IP) and/or Constraint Programming (CP) models, where the best method depends on the characteristics of the shop floor.

Torabi, Sahebjamnia, Mansouri, & Bajestani (2013) study the unrelated parallel machine scheduling problem with multiple objectives, related to total weighted flow time, total weighted tardiness and machine load variation. Furthermore, their problem considers setup times, non-zero ready times, due dates and uncertain processing times. The authors propose a Multi Objective PSO method. Compared against more conventional PSO methods, the proposed solution method outperforms the other PSO's in terms of effectiveness and efficiency when considering the three performance metrics. Abdeljaoued, Saadani, & Bahroun (2018) consider a similar problem with resource size and upper bound equal to one. The authors propose two heuristics and an SA meta-heuristic. SA reaches a near optimal solution when using the solution of the previously mentioned heuristic as input.

In case of scheduling in the semiconductor industry, reticles may be required as an additional resource, which is examined by Cakici & Mason (2007). To this extent, the authors develop four heuristics to solve the problem, two of them using approaches typically found in literature and the other two based on a two-phase heuristic. The best construction heuristic, combined with an improvement phase shows results that are 0.78% from optimal and

Table 4
Parallel machine scheduling with fixed resources.

References	$\alpha\mid\beta\mid\gamma$ Notation	Approach
Garey & Johnson (1975)	$P2\mid res\cdot\cdot\cdot, p_j=1\mid C_{\max}$	Polynomial Solvable $O(m^3)$
Blazewicz (1979)	$P\mid res\cdot\cdot\cdot, r_j, d_j\mid$	Polynomial Solvable $O(n^2)$
Blazewicz et al. (1983)	$Q2\mid res1\cdot\cdot, p_j=1\mid C_{\max}$	Polynomial Solvable $O(n\log n)$
	$Q\mid res1\cdot 1, p_j=1\mid C_{\max}$	Polynomial Solvable $O(n^3)$
	$P3\mid res\cdot 11, p_j=1\mid C_{\max}$	NP-Hard
	$Q2\mid res\cdot 11, p_j=1\mid C_{\max}$	NP-Hard
Błazewicz et al. (1986)	$P2\mid res1\cdot\cdot, p_j=1\mid C_{\max}$	NP-Hard
	$P2\mid res\cdot 11, p_j=1\mid C_{\max}$	NP-Hard
Błażewicz et al. (1987)	$P\mid res1\cdot 1\mid \sum C_j$	Polynomial Solvable $O(n^3)$
	$P2\mid res1\cdot\cdot\mid \sum C_j$	NP-Hard
	$P2\mid res\cdot\cdot 1\mid \sum C_j$	NP-Hard
Brucker & Krämer (1996)	$P\mid res\cdot\cdot\cdot, types=R; p_j\le p\mid \sum w_jC_j, \sum T_j, \sum w_j, U_j$	Polynomial Solvable $O(R(p+s)n^{Rp}+R^2pn^{R(p+2)})$
	$P\mid res\cdot\cdot\cdot, p_j\le p, types=R, r_j\mid C_{\max}, \sum C_j$	Polynomial Solvable $O(R(p+s)n^{Rp}+R^2pn^{R(p+2)+1})$
	$Pm\mid res\cdot\cdot\cdot, types=R\mid \sum w_jC_j, \sum T_i, \sum w_j, U_i$	Polynomial Solvable $O(msR^m+m(m+R)R^{m+1}n^{R(m+1)})$
	$Pm\mid res\cdot\cdot\cdot, types=R; r_j\mid C_{\max}, \sum C_j$	Polynomial Solvable $O(msR^m+m(m+R)R^{m+1}n^{R(m+1)+m})$
Kovalyov & Shafransky (1998)	$Q\mid res1\cdot 1, p_j=1\mid C_{\max}$	NP-hard
	$Q\mid res1\cdot 1, p_j=1, nmit\mid C_{\max}$	Polynomial Solvable $O(m\log m)$
Ventura & Kim (2000)	$P\mid res1\cdot 1, p_j, d_j=d\mid TAD$	Polynomial Solvable $O(n^4)$
Błażewicz et al. (2001)	$P\mid res1\cdot 1\mid \sum C_j$	Polynomial Solvable $O(n^3)$
Ventura & Kim (2003)	$P\mid res1\cdot 1, r_j, p_j, d_j=d\mid TADD$	Polynomial Solvable $O(n^4)$
Kellerer & Strusevich (2003b)	$PD2\mid res111\mid C_{\max}$	Polynomial Solvable $O(n)$
	$Pd_j\mid res111\mid C_{\max}$	Group Technology Algorithm & PTAS $O(n)$
	$PD3\mid res111\mid C_{\max}$	NP-Hard
	$PD\mid res111\mid C_{\max}$	NP-Hard
	$PD3\mid res111\mid C_{\max}$	Heuristic Approximation Algorithm
	$PD4\mid res111\mid C_{\max}$	Heuristic Approximation Algorithm
Kellerer & Strusevich (2003a)	$PD2\mid res211\mid C_{\max}$	Polynomial Solvable $O(n)$
	$PD2\mid res1\cdot\cdot\mid C_{\max}$	Polynomial Solvable $O(n)$
	$PD2\mid res222\mid C_{\max}$	NP-Hard
	$PD2\mid res311\mid C_{\max}$	NP-Hard
	$PD\mid res\lambda 11\mid C_{\max}$	Greedy Algorithm
	$Pd_j\mid res\lambda 11\mid C_{\max}$	PTAS
Slowinski (1988)	$R\mid res\cdot\cdot 1\mid \sum TC_j$	Two-Phase Method
Błazewicz et al. (1993)	$P2\mid res\cdot\cdot\cdot, p_j=1\mid L_{\max}$	Branch and Bound
Srivastav & Stangier (1997)	$P\mid res\cdot\cdot 1, r_j, p_j=1\mid C_{\max}$	PTAS
Józefowska et al. (2002)	$PD\mid res1\cdot, cdot\mid C_{\max}$	TS/Heuristics
Ventura & Kim (2003)	$P\mid res\cdot\cdot\cdot, p_j=1, d_j, r_j\mid TADD$	Lagrangian Relaxation
Cakici & Mason (2007)	$Pm\mid res1\cdot\cdot, r_j\mid \sum w_jC_j$	Heuristics
Edis et al. (2008)	$P\mid res1\cdot 2, M_j, p_j=1\mid \sum C_j$	Lagrangian and problem based heuristic
Edis & Ozkarahan (2011)	$P\mid res1\cdot 2, M_j\mid C_{\max}$	IP, CP and IP/CP
Edis & Ozkarahan (2012)	$P\mid res1\cdot 2, M_j\mid C_{\max}$	IP/IP and IP/CP
Edis & Oguz (2011)	$R\mid res1\cdot\cdot\mid \sum C_j$	IP, Lagrangian Relaxation, IP/CP
Torabi et al. (2013)	$R\mid res\cdot\cdot\cdot, r_j, S_j\mid z(\sum_{i=1}^{N} w_iF_i, \sum_{i=1}^{N} w_iT_i, \sum_{n=1}^{M} D(\sum C, C_{\max})$	MOPSO
Bitar et al. (2016)	$R\mid res1\cdot 1, M_j, S_j\mid \sum w_jC_j$	MA
Ham (2018)	$R\mid res1\cdot 1, M_j, S_j\mid \sum w_jC_j$	CP, MIP/CP, CP with Order based Heuristic
Zheng & Wang (2016a)	$R\mid res1\cdot 1, S_j, f_i\mid C_{\max}$	Two Stage Adaptive FFO
Zheng & Wang (2018)	$R\mid res1\cdot 1, S_j, f_i\mid z(C_{\max}, \sum E)$	FFO
Afzalirad & Rezaeian (2016)	$R\mid res\cdot\cdot\cdot, r_j, S_{ij}, M_j, Prec\mid C_{\max}$	GA, AIS
Villa et al. (2018)	$R\mid res1\cdot\cdot\mid C_{\max}$	Heuristics
Vallada et al. (2019)	$R\mid res1\cdot\cdot\mid C_{\max}$	Enriched Scatter Search, Enriched Iterated Greedy
Abdeljaoued et al. (2018)	$P\mid res\cdot 11\mid C_{\max}$	Heuristics, SA
Fanjul-Peyro et al. (2017)	$R\mid res1\cdot\cdot\mid C_{\max}$	MILP, Math-Heuristics
Fanjul-Peyro (2020)	$R\mid res3\cdot\cdot, S_j\mid C_{\max}$	MILP, 3-Phase Algorithm
Akyol Ozer & Sarac (2019)	$P\mid res\cdot\cdot 1, S_j, M_j\mid \sum w_jC_j$	Mathematical Model, GA

that provides the best results in 76 out of the 80 total tested instances. Bitar, Dauzère-Pérès, Yugma, & Roussel (2016), Ham (2018), Zheng & Wang (2016a) and Zheng & Wang (2018) study similar problems within the semi-conductor industry. All authors propose different solution methods, however no comparison between results is given. Afzalirad & Rezaeian (2016) also study a problem from industry, namely the block erection scheduling problem in a shipyard. Next to additional resources, the authors also investigate non-zero release times, machine eligibility, precedence relations and setup times. To solve the problem, the authors propose two meta-heuristic methods, GA and an Artificial Immune System (AIS). Computational results showed that both algorithms are effective in small scale problems, but in large scale problems the AIS outperformed the GA.

Fanjul-Peyro, Perea, & Ruiz (2017) study an unrelated parallel machine scheduling problem with a limited number of resources and the objective to minimize the makespan. Both the processing times and resources depend on the machine and job assignment. Two MILP's and three math-heuristics are proposed, with the latter providing similar results in small test cases and outperforming both MILP models in medium test cases. Fanjul-Peyro (2020) study a similiar problem in the plastic moulding industry. This paper is unique as it considers three different resource types used during different moments in production. An MILP and a Three Phase Algorithm are introduced to solve the problem. This latter algorithm can solve large sized problems with up to 400 jobs. Fleszar & Hindi (2018) consider the same problem as Fanjul-Peyro et al. (2017) and develop a two-stage heuristic, based on both an MILP model and a CP model. Both models are effective in finding good solutions, with the CP model finding better solutions than the models by Fanjul-Peyro et al. (2017), while also showing good solutions for much larger problems. Akyol Ozer & Sarac (2019)

Table 5
Parallel machine scheduling with speeding-up resources.

References	$\alpha\|\beta\|\gamma$ Notation	Approach
Kellerer (2008)	$PD2\|res111, Bi\|C_{\max}$	NP-Hard
Daniels et al. (1996)	$P\|res1\cdot\cdot, Int\|C_{\max}$	Branch and Bound, Static Based Search
	$P\|res1\cdot\cdot, Stc\|C_{\max}$	Polynomial Solvable $O(n\log n)$
	$P\|res1\cdot\cdot\|C_{\max}$	Polynomial Solvable $O(n\bar{k}(n+m))$
Daniels et al. (1999)	$P\|res1\cdot\cdot, Stc\|C_{\max}$	Decomposition Heuristic, TS
Ruiz-Torres & Centeno (2007)	$P\|res1\cdot\cdot, Stc\|C_{\max}$	Heuristics, Lower Bound
Daniels et al. (1997)	$P\|res1\cdot\cdot, Stc\|C_{\max}$	Static Based TS, TS
Ólafsson & Shi (2000)	$P\|res1\cdot\cdot, Stc\|C_{\max}$	NPM
Grigoriev et al. (2005)	$R\|res1\cdot\cdot, Int\|C_{\max}$	Approximation Algorithm $(4+s\sqrt{2})$
	$PD\|res1\cdot\cdot, Int\|C_{\max}$	Approximation Algorithm $(3+2\sqrt{2})$
Kumar et al. (2005)	$R\|res1\cdot\cdot, Int\|C_{\max}$	Approximation Algorithm (4)
Grigoriev et al. (2006)	$R\|res1\cdot\cdot, Int\|C_{\max}$	Approximation Algorithm (3.75)
Grigoriev et al. (2007)	$R\|res1\cdot\cdot, Int\|C_{\max}$	Optimality Gap
	$R\|res1\cdot\cdot, Lin\|C_{\max}$	Approximation Algorithm $(3+\epsilon)$
Kellerer (2008)	$R\|res1\cdot\cdot, Int\|C_{\max}$	Approximation Algorithm (3.5)
Kellerer & Strusevich (2008)	$PD2\|res111, Bi\|C_{\max}$	Dynamic Programming, Approximation Algorithm (1.75)
	$Pd_j\|res1\sigma\sigma, Bi\|C_{\max}$	Approximation Algorithm (3)
Su & Lien (2009)	$P\|res1\cdot\cdot, Stc\|C_{\max}$	Heuristics
Edis & Oguz (2012)	$R\|res1\cdot\cdot, Int\|C_{\max}$	IP/CP
	$PD\|res1\cdot\cdot, Int\|C_{\max}$	IP/CP
Ruiz-Torres et al. (2007)	$Q\|res\cdot\cdot1, Stc\|\sum U_i$	Heuristics
Xu et al. (2011)	$P2\|res111, Bi\|C_{\max}$	FPTAS, Dynamic Programming
Chen et al. (2018)	$P\|res\cdot\cdot1, Int\|C_{\max}$	Approximation Algorithm (2)
Hsieh et al. (2015)	$Rm\|res1\cdot\cdot, d_j, Int\|z(\sum C_{ij}, TPC)$	Assignment Problem
	$Rm\|res1\cdot\cdot, d_j, Int\|z(\sum C^i_{\max}, TPC)$	Assignment Problem
	$Rm\|res1\cdot\cdot, d_i = d, d_j\|z(\sum(\alpha E_{ij} + \beta T_{ij}), TPC)$	Assignment Problem
Lu et al. (2016)	$R\|res\cdot\cdot\cdot, LDRA\|F$	$O(n^{m+2})$
Fu et al. (2018)	$P\|res1\cdot\cdot, Int\|C_{\max}$	Master-Slave GA
Fu et al. (2019b)	$P\|res1\cdot\cdot, Int\|C_{\max}$	NPM

consider a similar problem and develop two mathematical models and a math-heuristic based on GA. Their MILP is able to solve small instances only, whereas the math-heuristic provides good solutions for medium and large instances. Villa, Vallada, & Fanjul-Peyro (2018) study a uniform parallel machine scheduling problem. The authors assume that resource usage of jobs depends on the machine they are allocated to. This is relatively new in the field. In order to solve this problem, the authors propose two multi pass heuristics, both showing promising results, especially when considering larger sized problems. The authors continue their work in Vallada, Villa, & Fanjul-Peyro (2019). They enrich the previous algorithms with two local search methods, Enriched Scatter Search and Enriched Iterated Greedy. Compared to the solution method by Villa et al. (2018), the proposed algorithm outperforms for all test cases, both in terms of efficiency and effectiveness. A summary of all papers for parallel machine scheduling with fixed resources is given in Table 4.

3.2.2. Scheduling with speeding-up resource types

Daniels et al. (1996) are one of the first to study a dynamic scheduling problem, where the processing time depends on the number of assigned resources. The authors consider a parallel cell environment, where each cell contains a single machine. For this problem, a mathematical model is developed and an optimal algorithm is proposed. The dynamic problem is shown to be NP-hard when there are three or more machines and is solved through a B&B method. In later work, Daniels, Hua, & Webster (1999) consider the static version of the same problem as in Daniels et al. (1996). This time, a decomposition heuristic and TS are provided to solve the problem. Results show that TS outperforms the decomposition technique, obtaining results close to optimal in a reasonable amount of computational time. Ruiz-Torres & Centeno (2007) consider the same problem as Daniels et al. (1999). They provide new heuristics to solve the problem, which are combinations of traditional methods to solve the scheduling problem and new strategies to assign the resources. The authors also present a lower bound. The heuristics outperform previous solution methods and provide solutions close to the lower bound. Next, Daniels, Hoopes, & Mazzola (1997) continue their work and consider the same problem as stated before. The authors explore the use of a TS algorithm to solve the problem, review existing heuristics and develop two new ones. They show that combining TS with a Static Based TS results in a 0.5% gap to optimality on average over 1350 different problems. Ólafsson & Shi (2000) consider a similar problem as in Daniels et al. (1996). However, they propose a method referred to as the Nested Partitions Method (NPM). The authors state that their method provides high quality schedules, fast and for large-sized problems. In addition, they also state that benefits can be gained by using flexible resources instead of static resources. Chen (2004) investigate similar problems, assuming continuous and discrete processing times. The objective is to minimize the weighted number of tardy jobs and weighted completion time. The solution methods are capable of solving medium sized problems (40 jobs and any given number of machines) in a reasonable computation time.

Multiple studies provide approximation algorithms to solve dynamic problems for parallel machines. Grigoriev, Sviridenko, & Uetz (2005), Kumar, Marathe, Parthasarathy, & Srinivasan (2005), Grigoriev, Sviridenko, & Uetz (2006), Grigoriev, Sviridenko, & Uetz (2007), Kellerer (2008) and Grigoriev & Uetz (2009) consider similar problems where each study improves upon the approximation algorithms in earlier studies. Table 5 summarizes the results of these approximation algorithms. In addition, Kellerer & Strusevich (2008) consider generalized versions of the problems proposed by the previous authors and provide both Dynamic Programming (DP) approaches and approximation algorithms.

Su & Lien (2009) study the problem of identical parallel machines with linearly dependent processing times. In order to solve this problem, the authors develop multiple heuristics, with the best performing one showing an average solution quality of 99.65%. This heuristic first allocates the resources optimally and afterwards effectively assigns the jobs. Using a similar approach, Edis & Oguz (2012) study the dynamic problem where the processing time depends on the number of allocated resources. The proposed IP/CP model proves to be especially effective in larger sized problems. Xu, Xu, & Xie (2011) investigate the problem of two identical machines with speed-up resources. The processing time of a job depends on the resource allocated to it. The authors develop a fully PTAS (FPTAS) and a DP approach. Chen, Ye, & Zhang (2018) consider a more general case of the problem. When the number of resources is equal to the number of machines, a 2-approximation algorithm is provided. The authors also provide a PTAS for cases where the number of machines or the number of resources is constant.

Ruiz-Torres, López, & Ho (2007) study the uniform parallel machines scheduling problem with speeding-up resources. In order to solve this problem, the authors propose five different heuristics. Out of these five heuristics, the most dominant ones hold the specific property of loading machines with jobs one at a time. However, the performance of each heuristic depends heavily on the situation of the shop floor regarding due date tightness and other factors. Hsieh, Yang, & Yang (2015) consider an unrelated parallel machine scheduling problem with multiple objective functions. In addition, they study discrete resource allocation, where the processing time depends on the number of resources allocated to it. The authors consider three different problems and provide an assignment problem solvable in polynomial time for each of the problems. Lu, Jin, Ji, & Wang (2016) also consider the problem of unrelated parallel machines with the addition of deteriorating jobs and learning effects. The objective function F is a combination of the total load, total completion time and total absolute deviation of job completion time. Fu, Tian, Li, & Wang (2018) study the problem of a single resource type with integer resource processing time. The authors propose a Master-Slave GA, where the master chromosome represents the resource allocations and the accompanying slave chromosomes represent job assignments and sequences. Results show that the proposed method outperforms the methods proposed by Daniels et al. (1997) in terms of computational time and solution quality. In Fu, Jiang, Tian, & Wang (2019b), the authors consider the same problem, but propose a hybrid NPM. Similarly, compared to the methods of Daniels et al. (1997), their proposed solution method shows better results. A summary of all papers for parallel machine scheduling with speeding up resources is given in Table 5.

3.2.3. Discussion

Compared to both job shop and flow shop scheduling (as will be shown in Section 3.3), parallel machine scheduling has received a considerable amount of attention in the field. A lot of earlier work in the fixed resources category focused on providing polynomial solvable solutions to certain variants of the problem. Blazewicz (1979) delivers most research in this area, by looking at different resource constraints and either proposing PTAS or proving that a certain problem is NP-Hard. Later on, other studies consider the same problems and start improving on the approximation schemes. Recently, new studies start to focus more on (meta-)heuristics, where a diverse solution field can be seen. In addition, a switch can also be seen in the problem type, as the environment has changed from identical parallel machines to unrelated parallel machines. While some studies consider similar problems, the results are often not compared to each other, which is also observed in the job shop scheduling problem. Authors often only compare their improved solution methods to their previous ones. It therefore becomes difficult to see if one solution method outperforms another. In future work, it would therefore be useful to have a "standardized" benchmark, in order to compare different solution methods. Furthermore, another significant opportunity would be to consider different objective functions, as currently, minimization of the maximum makespan is considered in almost all cases.

Regarding speeding up resources, the same trend can be seen as with fixed resources. Earlier work considers mostly approximation algorithms, while newer work focuses mainly on heuristics. The problem field is also diverse, with studies examining different kinds of speeding up resources (i.e., integer, static, etc.). In addition, the studies also consider both identical and unrelated parallel machines. However, only a single study considers uniform machines. Furthermore, it is noticed that the objective function is again the minimization of the maximum makespan. It will therefore be interesting to investigate other objective functions that are often considered in practice, such as tardiness. Furthermore, almost all studies consider the scheduling of a single resource, while in practice, multiple resources have to be considered during scheduling. Thus, extending the number of resources is another major opportunity. Lastly, similar to fixed resources and the field of job shop scheduling, a benchmark and a comparison of results should also be considered.

3.3. Flow shop

This section considers a flow shop environment, for both fixed and speeding up resource types. An overview of the literature in this section is given in Table 6. Flow shop scheduling with additional constraints is not researched as extensively as job shops or parallel machines. One of the first studies is from Elvers & Treleven (1985), as is previously mentioned in Section 3.1.1. The authors conclude that dispatching rules that work well for job shop environments can also be applied to flow shops. Much later, Daniels, Mazzola, & Shi (2004) study the problem of flow shop scheduling under partial resource flexibility. This partial flexibility results from, e.g., cross trained workers. Each worker has a different skillset which determines the machine or job a worker can work on. In this case, Daniels et al. (2004) state that the processing time depends on the number of trained workers assigned to a certain job or operation. Results show that a small investment in worker flexibility can lead to significant benefits. In addition, they show that the mix of skills highly influences production performance and that skills derived from training workers on consecutive stations are particularly effective.

Figielska (2006, 2008, 2009, 2010, 2014, 2018) consider similar problems within flow shop scheduling. These problems are related to a two-stage flow shop. Most of the studies consider a similar resource constraint, with a single unit of resource which can be used for processing. An exception is the study by Figielska (2009), where this constraint is dropped. The author continuously improves upon previous work, expanding from unrelated parallel machines in the first stage and a single machine in the second stage, to both stages containing unrelated parallel machines. Most notably, in Figielska (2014) and Figielska (2018), both preemption and commonly shared resources between stages are considered. All papers draw similar conclusions regarding the results, where the quality of the solution or the best solution method depends on the characteristics of the flow shop (e.g., number of machines or number and types of resource constraints).

Logendran (2013) studies the flow shop scheduling problem where the additional resource is labor. The workforce is multi-skilled and sequence-dependent setup times are also considered. Furthermore, jobs are able to skip certain stages within the flow shop. The author presents a mathematical model and a meta-heuristic algorithm. Results show close to optimal solutions for small sized problem instances. Waldherr & Knust (2017), on the other hand, study a synchronous flow shop comprising both resources and setups, which is a special case of the flow shop problem. The authors propose two decomposition heuristics, which hi-

Table 6
Flow shop scheduling with resources.

References	$\alpha\|\beta\|\gamma$ Notation	Approach
Elvers & Treleven (1985)	-	Dispatching Rules
Daniels et al. (2004)	-	Worker Flexibility
Figielska (2006)	$F2\|res\cdot\cdot1\|C_{\max}$	Two-Step Algorithm (Two Stage and GA)
Figielska (2008)	$F2\|res\cdot\cdot1\|C_{\max}$	Two-Step Algorithm (Two Stage and Linear Programming)
Figielska (2009)	$F2\|res\cdot\cdot\cdot\|C_{\max}$	Two-Step Algorithm (Column Generations and GA/SA)
Figielska (2010)	$FH2\|res\cdot\cdot1\|C_{\max}$	Two-Step Algorithm(Two-Stage and Linear Programming)
Figielska (2014)	$FH2\|res\cdot\cdot1, prem\|C_{\max}$	Priority Rules and CG/TS/Greedy Procedure
Figielska (2018)	$FH2\|res\cdot\cdot1, prem\|C_{\max}$	Heuristic Method
Logendran (2013)	$FH\|res\cdot\cdot1, ST_{st}\|C_{\max}$	Mathematical Model and Meta Heuristic
Waldherr & Knust (2017)	$SF\|res\cdot\cdot1, ST_{st}\|C_{\max}$	Decomposition Heuristic

erarchically solve both the job sequencing and resources assignment problem. Results show that the solution quality of the heuristics depends on the data, thus on information related to, for example, setups. A summary of all papers for flow shop scheduling with resources is given in Table 6.

3.3.1. Discussion

Flow shop scheduling with either fixed or speeding-up resources has only been considered rarely, with Figielska (1999) leading the field with six different studies (out of the ten that are found). It is therefore difficult to asses this field, as the same problem is studied with a similar solution method. It can be seen that both normal and hybrid flow shops are studied. Clearly, there is a lot of opportunity to both diversify the field and to introduce benchmarks which can be used in later studies. This includes the study of linear, static and binary resources, using tardiness as an objective function and using meta heuristics such as GA or ACO as a solution approach.

3.4. Takeaways; integrated production and resource scheduling

The main takeaways of the survey on integrated scheduling of production and resources are given below:

- Job shop and parallel machine environments are studied thoroughly, whereas the literature concerning flow shops is scarce.
- Literature on job shop scheduling focuses mainly on DRC scheduling, taking workers into account. Within this category, the main focus is on heterogeneous workers (i.e., speeding up resource). In comparison, within the parallel machine environment, the main focus is on fixed resources.
- Literature regarding job shops mostly study the effect of workers on production through the use of worker assignment rules. Regarding solution methods, the focus is on meta-heuristics. In comparison, within the parallel machine environment, more diverse solution methods are encountered.
- For the parallel machine environment, the problem field is diverse. Within job shops however, mainly the DRC problem is considered. Also, the same problem type is often considered in the job shop environment, as resource attributes are often similar. Difference is made in the flexibility of the workforce. Within flow shops, only two or three different problems are considered.
- Studies based on real world problems with real-life data are scarce.

4. Maintenance

In this section, literature regarding the integrated maintenance and production scheduling problem is considered. The section is divided into three sections, each reviewing a different machine environment. The machine environments (Flexible) Job Shop and Open Shop (4.1), Parallel Machines (4.2) and (Flexible) Flow Shop (4.3) are considered.

4.1. (Flexible) job shop and open shop

This section considers a job/open shop environment and divides maintenance scheduling into the categories ‘Scheduling with an RMA’ (4.1.1), ‘Scheduling in a flexible window’ (4.1.2), ‘Scheduling before reaching machine age’ (4.1.3) and ‘Scheduling with a PM policy’ (4.1.4). An overview of the considered literature is provided in Table 7.

4.1.1. Scheduling with an RMA

Kubzin & Strusevich (2006) are the first to consider a deteriorating maintenance activity for the two-machine open shop. They show that the open shop problem with one linear time-dependent RMA on the first machine can be solved in linear time. As they are the first to consider this problem, they only provide algorithms that may serve as subroutines for other heuristics. Abedi, Chiong, Noman, & Zhang (2020) are the first and only to consider deteriorating jobs in a job shop. In their setting, each machine has a number of speed levels and the processing time depends on both the selected speed level and the cumulative deterioration of the machine. Deterioration of a job is modeled by considering both job and position-dependent deterioration simultaneously. The RMA restores the machine to its original state. In addition, they also need to determine the appropriate speeds of the machines to minimize the energy consumption. An MILP is derived and a hybrid Multi Objective MA (MOMA) is presented that outperforms other existing algorithms in the literature.

4.1.2. Scheduling in a flexible window

The works of Youssef, Brigitte, & Noureddine (2003), Ali, Sassi, Gossa, & Harrath (2011), Gao, Gen, & Sun (2006), Rajkumar, Asokan, & Vamsikrishna (2010), Li & Pan (2012), Li, Pan, & Tasgetiren (2014), Ziaee (2014), Dalfard & Mohammadi (2012), Lei (2013), Zheng, Lian, & Mesghouni (2014) and Mosheiov, Sarig, Strusevich, & Mosheiff (2018) consider scheduling maintenance in a flexible window. The study by Youssef et al. (2003) is the first to introduce maintenance activities that must be scheduled flexibly in a window within the job/open shop environment. In their work, maintenance can be advanced or delayed beyond the flexible window, which comes at a cost in the form of a penalty. They provide lower bounds for the makespan criterion and use a multi-objective GA on publicly available data sets. The work of Youssef et al. (2003) is extended by Ali et al. (2011), that changes one aspect of the maintenance scheduling constraint. When maintenance is advanced or delayed, the interval shifts accordingly to this advance or delay. All studies, except for the work of Youssef et al. (2003) and Ali et al. (2011), consider maintenance in strict time windows, i.e., to advance or delay beyond this window is not allowed. The studies that don’t consider strict windows impose maintenance earliness and tardiness costs on the objective function. In the studies

Table 7
(Flexible) job shop and open shop scheduling with maintenance.

Maintenance Type	References	$\alpha\|\beta\|\gamma$ Notation	Approach
RMA	Kubzin & Strusevich (2006)	$O2\|RMA_{m-time-1-1}\|C_{\max}$	Polynomial Solvable $O(nm)$
	Abedi et al. (2020)	$J\|d_j, RMA_{j-pos-job}\|z(\sum TE_j, \sum w_jT_j)$	MILP, MOMA
Window	Youssef et al. (2003)	$J\|h_{(win-flex-m)}\|z(C_{\max}, \sum EC_m, \sum TC_m)$	Establish lower bounds
	Mosheiov et al. (2018)	$O2\|h_{(win-flex-1-2)}\|C_{\max}$	Approximation algorithm (1.5)
	Rajkumar et al. (2010)	$FJ\|nr, h_{(win-flex-m)}\|C_{\max}, W_{\max}, \sum Wm_j$	GRASP
	Wang & Yu (2010)	$FJ\|nr, h_{(win-flex-m)}\|C_{\max}, W_{\max}, \sum Wm_j$	FBS
	Li & Pan (2012)	$FJ\|nr, h_{(win-flex-m)}\|C_{\max}, W_{\max}, \sum Wm_j$	DCRO
	Li et al. (2014)	$FJ\|nr, h_{(win-flex-m)}\|C_{\max}, W_{\max}, \sum Wm_j$	DABC
	Ziaee (2014)	$FJ\|h_{(win-flex-1)}\|C_{\max}, W_{\max}, \sum Wm_j$	Constructive heuristic
	Lei (2013)	$J\|d_j, nr, p_{int}, h_{(win-flex-m)}\|z(C_{\max}, \sum T_j)$	ABC
	Ali et al. (2011)	$J\|h_{(win-flex-m)}\|z(C_{\max}, \sum EC_m, \sum TC_m)$	GA
	Zheng et al. (2014)	$FJ\|h_{(win-flex-m)}\|C_{\max}$	GA, ACO, ABCO
	Gao et al. (2006)	$FJ\|nr, h_{(win-flex-m)}\|C_{\max}, W_{\max}, \sum Wm_j$	HGA
	Dalfard & Mohammadi (2012)	$FJ\|r_j, d_j, h_{(win-flex-m)}\|z(C_{\max}, \sum T_j, \sum E_j)$	HGA, MILP, SA
Age	Golmakani & Namazi (2012)	$J\|r, h_{(age-flex-m)}\|C_{\max}$	AIS
	Fitouri et al. (2016)	$J\|h_{(age-job-flex-m)}\|z(C_{\max}, \sum CM_m)$	Heuristic
PM Policy	Naderi et al. (2009a)	$J\|ST_{sd}, FR_{Weibull}, Rlb_{\min}\|C_{\max}$	GA, SA
	Moradi et al. (2011)	$FJ\|FR_{Exp}\|z(C_{\max}, Avb_{\max})$	GA
	Chen et al. (2020)	$FJ\|FR_{Weibull}, Rlb_{\min}\|\mathcal{F}$	GA, MILP
	Azadeh et al. (2015)	$O\|FR_{poisson}, Avb_{\max}\|\mathcal{F}$	GA, PSO, MILP
	Mokhtari et al. (2012)	$J\|FR_{Exp}\|z(C_{\max}, Avb_{\max})$	PVNS
	Naboureh & Safari (2016)	$O\|ST_{sd}, FR_{Weibull}, Rlb_{\min}\|C_{\max}$	AIS

by Ziaee (2014) and Mosheiov et al. (2018), only one maintenance activity per machine is considered, whereas in the other studies, the problem of multiple maintenance activities per machine is examined. All studies associate one flexible window to each maintenance activity. Though, the interval between two consecutive maintenance activities varies per study. In most studies, a fixed interval is considered. Youssef et al. (2003) propose both a fixed interval and an interval depending on the workload of the jobs, while Zheng et al. (2014) generate maintenance activities based on condition based maintenance. All studies propose a meta-heuristic solution specifically designed for their maintenance scheduling constraint and objective function. Mosheiov et al. (2018) is the only study to instead develop approximation algorithms. In addition, the study by Dalfard & Mohammadi (2012) also proposes an MILP solution.

Gao et al. (2006), Rajkumar et al. (2010), Wang & Yu (2010) Li & Pan (2012), Li et al. (2014) and Ziaee (2014) study the same problem. A flexible job shop with nonresumable jobs is considered where maintenance must be scheduled flexibly. Three different objectives are analyzed separately, namely $C_{\max}$, $W_{\max}$ and $\sum Wm_j$. Gao et al. (2006) show that their HGA is more effective compared to other classical algorithms such as GA, PSO and SA for all three objectives. Rajkumar et al. (2010) extend on Gao et al. (2006) and propose a GRASP algorithm for the similar problem and objectives. They show that for the same problem instances, their solution method performs better on $\sum Wm_j$ but worse or equally good on the other objectives. The FBS proposed by Wang & Yu (2010) performs better for the workload objectives and worse for $C_{\max}$. Li & Pan (2012) and Li et al. (2014) propose a DCRO and DABC, respectively. Both solution methods perform equally good as the HGA of Gao et al. (2006) for the same problem instances. Additionally, Li et al. (2014) extend the benchmark to larger-sized problem instances of other studies and include the HGA of Gao et al. (2006). The DABC outperforms the HGA on one particular instance only, while for all other instances the same results are obtained. The study by Ziaee (2014) adapts the problem by considering the three objectives simultaneously, making it a multi-objective problem. A heuristic based on a constructive procedure is presented. The heuristic is compared to the previously mentioned HGA and GRASP by adding arbitrary weights. It is shown that the heuristic outperforms the other solution methods for two of the four problem instances.

4.1.3. Scheduling before reaching machine age

A multiple-route job shop scheduling problem is studied by Golmakani & Namazi (2012). Maintenance is performed before the machine's maximum age. Perfect PM is considered and only jobs affect the machine age, i.e., idle time does not advance the machine age. The authors present an ILP and an AIS. Experiments on randomly generated data show that the AIS obtains better solutions in a reasonable amount of time. A different maintenance model is proposed by Fitouri, Fnaiech, Varnier, F.Fnaiech, & Zerhouni (2016). In their work, each machine has a level of degradation and based on this level, the RUL is determined. Each operation induces a degradation that depends on the type of operation. Degradation cannot exceed a certain threshold value. Perfect PM is performed before reaching this threshold. In addition, some operations cannot be preempted while others are resumable. A heuristic solution method with different decision rules is presented for the problem. They conclude that the solution depends on the choice of the decision rule.

4.1.4. Scheduling with a PM policy

The studies by Naderi, Zandieh, & Fatemi Ghomi (2009a), Mokhtari, Mozdgir, & Abadi (2012), Moradi, Fatemi Ghomi, & Zandieh (2011), Chen, An, Zhang, & Li (2020), Azadeh, Farahani, Kalantari, & Zarrin (2015) and Naboureh & Safari (2016) schedule PM according to a PM policy. The approach proposed in Ruiz, Carlos García-Díaz, & Maroto (2007) (discussed in more detail in Section 4.3.4) is adopted by Naderi et al. (2009a) and Naboureh & Safari (2016). Three maintenance policies are considered: (1) policy I: preventive maintenance at fixed predefined time intervals, (2) policy II: optimum period model for the preventive maintenance maximizing the machines availability and (3) policy III: maintaining a minimum reliability threshold for a given production period t. In both studies, the conservative criterion as mentioned in Ruiz et al. (2007) is used for scheduling maintenance. This criterion implies that whenever a job is to be processed on a machine, the total accumulated processing time is determined. Then, if this time is higher than the PM interval time obtained in the step before scheduling, the job is postponed and PM is carried out first, i.e., PM is advanced. A GA and SA are presented by Naderi et al. (2009a) while Naboureh & Safari (2016) propose an AIS to solve the problem. The approach proposed by

Berrichi, Amodeo, Yalaoui, Châtelet, & Mezghiche (2009) (discussed in more detail in Section 4.2.4) is used in the studies of Mokhtari et al. (2012) and Moradi et al. (2011). In this approach, both the minimization of makespan and the maximization of system availability of the whole system are considered simultaneously. Mokhtari et al. (2012) extend the problem of Berrichi et al. (2009) to the job shop environment while Moradi et al. (2011) extend it to the flexible job shop environment. Both studies propose meta-heuristic solutions to the problem. The GA presented by Moradi et al. (2011) is new for this problem, compared to the GA proposed by Berrichi et al. (2009), as it is hybridized with a composite dispatching rule. Also, the population-based VNS (PVNS) by Mokhtari et al. (2012) has not been used for this problem before. Where Moradi et al. (2011) adopts the rational criterion presented by Berrichi et al. (2009) to schedule maintenance, Mokhtari et al. (2012) conversely first generate a job schedule where maintenance is inserted afterwards. Azadeh et al. (2015) propose a different approach for the PM policy, compared to the policies of Ruiz et al. (2007) and Berrichi et al. (2009). The authors consider the reliability of the machine as part of the objective function where maintenance is perfect and restores the reliability completely. Chen et al. (2020) also present a different PM policy for the flexible job shop. They consider three operating states: (1) operating state in which no maintenance is performed, (2) operating state where maintenance must be performed and (3) operating state which is forbidden, but for which maintenance must be performed immediately. The operating state is determined by the machine reliability, which is modeled through a Weibull distribution. If the machine falls in state 2, PM is performed either before or after the next operation, based on the following mechanism: a maintenance advance and delay selection for $YZ \in [0, 1]$ is introduced. If $rand[0, 1] \leq YZ$, PM is performed before the next operation. In case the operating state falls in the third state, PM is performed immediately, i.e., before the next operation. The studies of Moradi et al. (2011), Chen et al. (2020) and Azadeh et al. (2015) use publicly available datasets for their experiments while Naboureh & Safari (2016), Mokhtari et al. (2012) and Naderi et al. (2009a) use artificial instances and explain how these can be generated.

4.1.5. Discussion

Literature on scheduling with an RMA in a job shop is scarce. The main study in this category by Kubzin & Strusevich (2006) has not received any significant follow-up. On the other hand, as discussed later, for flow shops and parallel machines, significantly more studies with various RMA constraints exist. Many of the RMA scheduling problems addressed in the other machine environments are applicable to the job shop. These can help to diversify the studies on RMA in a job shop environment.

Literature on scheduling maintenance within a flexible window has received serious attention. Many different aspects, which provide a clear overview of the challenges and versatility in this field, are addressed. For instance, both the cases with one and multiple maintenance activities per machine are considered and different approaches for the interval between two consecutive maintenance activities are studied. The pioneering work by Youssef et al. (2003) has been significantly extended. However, due to a lack of benchmarking, no clear picture can be created of the best solution method. In addition, not all problem types have received similar follow-up as that of Youssef et al. (2003). The most important opportunity is to conduct more research to understand the best solution method for different problem variants. All current research considers one single flexible window for maintenance. It would be interesting and relevant to study the problem with multiple flexible windows.

Literature on scheduling maintenance before it reaches a certain age is scarce as only two studies are performed. Both studies are interesting, but at the same time very different. Only the study by Fitouri et al. (2016) is suited for extension by means of benchmarking. At present, the number and diversity of studies in this category is too low to obtain a clear understanding of the challenges within this area of research. The major opportunity in this category is to perform more research.

Studies on scheduling with a PM policy consider different environments, objective functions and constraints. Novel elements have been introduced such as the use of new meta-heuristic solution methods by Moradi et al. (2011) and Mokhtari et al. (2012) and the introduction of a new reliability problem by Azadeh et al. (2015). At the same time, this diversity results in a lack of benchmarking. Currently, no main study or a state-of-the- art can be identified yet. More research is required to better understand which method is best suited for different problem variants.

4.2. Parallel machines

This section considers the parallel machines environment and divides maintenance scheduling into the categories ‘Scheduling with an RMA’ (4.2.1), ‘Scheduling in a flexible window’ (4.2.2), ‘Scheduling before reaching machine age’ (4.2.3), ‘Scheduling with a PM policy’ (4.2.4) and some special combinations (4.2.5). An overview of the considered literature is provided in Table 8.

4.2.1. Scheduling with an RMA

The study by Zhao, Tang, & Cheng (2009) is the first to consider an RMA on parallel machines. They study the case where only one RMA is scheduled per machine. Each job has two processing times: one in case it is scheduled before the RMA and another in case it is scheduled after the RMA, denoted by p_j and $\alpha_j p_j$, respectively, where α_j is the rate-modification factor of job j. Zhao, Guo, & Hsu (2011) extend the work to more than two parallel machines. Hsu, Cheng, & Yang (2011), Wang & Wei (2011) Cheng, Hsu, & Yang (2011), Wang, Wang, & Liu (2011), Yang, Hsu, & Yang (2012c), Wang, Huang, Ji, & Feng (2014), Yang, Hsu, & Yang (2014b), Yang, Cheng, & Yang (2014a), Yang, Lee, & Yang (2012b), Ma, Sun, Zeng, & Ning (2015b), Ma, Sun, Liu, & Wu (2015a) and Li & Wang (2018) address a similar maintenance problem. In these studies, a job has two processing times depending on its position with respect to the RMA. Hsu et al. (2011) extend the work of Zhao et al. (2009) to the unrelated parallel machine environment. They show that the cases where the rate-modification factor α_j is between 0 and 1, and larger than 0, can be solved in $O(n^{m+3})$ and $O(n^{2m+2})$ time, respectively. In the note on Hsu et al. (2011) by Yang et al. (2014b), it is shown that if the rate-modification factor is larger than 1, the problem can be optimally solved in $O(n^{m+3})$ time. The study by Ji & Cheng (2010) extends on Zhao et al. (2009) by considering multiple RMA's per machine, where the rate modification factor α_{ijk} also depends on the kth RMA on machine i. Ji & Cheng (2010) also examine learning effects on the jobs. Similar to Ji & Cheng (2010), the study by Yang & Yang (2013) considers multiple RMA's per machine. In their setting, the processing time of a job is p_{ij} before any RMA and $b_{ijr_g} p_{ij}$ if it starts immediately after the gth RMA which is scheduled in position r. In Yang et al. (2014a), a job has two processing times, either a_{ij} or b_{ij}, so the rate-modification factor is omitted. Yang et al. (2014a) extend the problem by considering controllable processing times. Yang et al. (2012b) also adopt the processing time approach of Yang et al. (2014a) and extend the basic problem by introducing a common due date. Wang & Wei (2011) build on Zhao et al. (2009) by considering an RMA with a duration that is a linear function of its starting time. They consider the total absolute deviation of completion times as an objective. Wang et al. (2011) consider a similar RMA, but apply this to the problem of Yang et al. (2014a). Li & Wang (2018) extend the study

Table 8
Parallel machine scheduling with maintenance.

Maintenance Type	References	$\alpha\|\beta\|\gamma$ Notation	Approach
RMA	Zhao et al. (2009)	$P2\|RMA_{j-pos-1-n}\|\sum C_j$	Polynomial Solvable $O(n^{2m+3})$
		$P2\|RMA_{j-pos-1-n}\|\sum w_jC_j$	Polynomial Solvable $O(nT^{3m})$
	Zhao et al. (2011)	$P\|RMA_{j-pos-1-n}\|\sum C_j$	Polynomial Solvable $O(n^{m+3})$
	Yang (2011)	$P\|RMA_{j-pos-1-n}\|\sum Wm_j$	Polynomial Solvable $O(n\log(n))$, $O(n^3)$
	Ji & Cheng (2010)	$P\|LR, RMA_{j-job}\|\sum Wm_j$	Polynomial Solvable $O(n^{m+2+\sum_{j=1}^{m} u_j})$
	Hsu et al. (2011)	$R\|RMA_{j-pos-1-n}\|\sum C_j$	Polynomial Solvable $O(n^{m+3})$, $O(n^{2m+2})$
	Yang et al. (2014b)	$R\|RMA_{j-pos-1-n}\|\sum C_j$	Polynomial Solvable $O(n^{m+3})$
	Yang et al. (2014a)	$R\|CP, RMA_{j-pos-1-n}\|z(\sum C_j, \sum CT_j)$	Polynomial Solvable $O(n^{m+3})$
	Yang et al. (2012b)	$R\|d_j, RMA_{j-pos-1-n}\|z(\sum TC_j, \sum EC_j)$	Polynomial Solvable $O(n^{2m+2})$
	Lee et al. (2013)	$R\|d_j, RMA_{j-pos-1-n}\|z(\sum TC_j, \sum EC_j)$	Polynomial Solvable $O(mn^3)$
	Yang et al. (2012a)	$R\|RMA_{j-pos}\|\sum Wm_j$	Polynomial Solvable $O(n^{m+3})$
	Yang & Yang (2013)	$R\|RMA_{j-pos}\|\sum C_j, \sum W_j$	Polynomial Solvable $O(n^{3+\sum_{i=1}^{m} k_i})$
	Wang (2013)	$R\|RMA_{j-pos}\|\sum Wm_j$	Polynomial Solvable $O(n^{m+4})$
	Ma et al. (2015b)	$P\|RMA_{j-pos-1-n}, RMA_{m-time}\|\sum Wm_j, \sum C_j, \sum TADC_j$	Polynomial Solvable $O(n^{2m-1}nlog(n))$
	Ma et al. (2015a)	$P\|RMA_{j-pos-1-n}, RMA_{m-time}\|z(\sum Wm_j, \sum C_j, \sum TADC_j)$	Polynomial Solvable
	Cheng et al. (2011)	$R\|RMA_{m-1-n}\|\sum Wm_j, \sum C_j$	Polynomial Solvable $O(n^{m+3})$
	Yang et al. (2012c)	$R\|RMA_{m-1-n}\|\sum Wm_j, \sum C_j$	Polynomial Solvable $O(n^{m+3})$
	Wang & Wei (2011)	$P\|RMA_{j-pos-1-n}, RMA_{m-time}\|\sum TADC_j, \sum TADW_j$	Polynomial Solvable $O(n^{2m+2})$
	Wang et al. (2011)	$P\|RMA_{j-pos-1-n}, RMA_{m-time}\|\sum C_j$	Polynomial Solvable $O(n^{2m+3})$
	Li & Wang (2018)	$P\|RMA_{j-pos-1-n}, RMA_{m-time}\|z(\sum C_j, \sum Wm_j)$	Polynomial Solvable $O(n^{2m+3})$
	Wang et al. (2014)	$R\|RMA_{j-pos-1-n}, RMA_{m-time}\|\sum C_j$	Polynomial Solvable $O(n^{m+3})$
	Hsu et al. (2013)	$R\|nr, RMA_{m-time-1-n}, RMA_{j-time}\|\mathcal{F}$	Polynomial Solvable $O(n^{2m+2})$
	Yang (2013)	$R\|RMA_{m-time}, RMA_{j-pos-job}, RMA_{j-time}\|\sum C_j$	Polynomial Solvable $O(n^{m+k+2})$
	Gara-Ali et al. (2016)	$R\|RMA_{j-pos}, RMA_{m-time}\|\mathcal{F}$	Polynomial Solvable $O(n^3+mn^2)$
	Wang & Li (2018)	$R\|RMA_{m-time}, RMA_{j-time}\|\sum C_j, \sum TADC_j$	Polynomial Solvable $O(n^{2m+2})$
	Zhang et al. (2018)	$P\|RMA_{m-time}, RMA_{j-pos}\|C_{\max}$	Polynomial Solvable $O(n^{m+k_0+2})$
	Xu et al. (2010)	$P\|RMA_{m-time}\|C_{\max}$	Approximation algorithm $max\{2(T_2+a)/(T_1+a), 4\}$
	Grigoriu & Briskorn (2017)	$P\|RMA_{m-time-job}\|C_{\max}$	Approximation algorithm (2), Heuristic
	Woo et al. (2017)	$R\|RMA_{j-time}\|C_{\max}$	GA, MILP
	Abedi et al. (2017)	$R\|M_j, RMA_{j-pos}\|z(\sum TC_j, \sum EC_j, \sum CM_m)$	GA, ICA
	Woo & Kim (2018)	$P\|RMA_{j-time}\|C_{\max}$	GA, MILP, SA
	Da et al. (2016)	$Q\|RMA_{j-time}, FR_{Weibull}\|z(\sum T_j, \sum CM_m)$	GA
	Chan et al. (2006a)	$FMS\|RMA_{m-time}\|C_{\max}$	GA
	Chan et al. (2006b)	$FMS\|RMA_{m-time}\|C_{\max}$	GA
	Chung et al. (2009)	$FMS\|IM, RMA_{m-time}\|z(C_{\max}, Rlb_{\min})$	GA
	Poongothai et al. (2019)	$R\|RMA_{j-time}, RMA_{j-pos}\|\sum C_j$	MIP
	Tian et al. (2019)	$P\|RMA_{m-pos}\|C_{\max}$	ILP
	Khalid & Yusof (2014)	$FMS\|RMA_{m-time}\|C_{\max}$	AIS
	Lu et al. (2018)	$R\|RMA_{m-time}, RMA_{j-time}\|C_{\max}$	Hybrid ABC and TS
Window	Lee et al. (2015)	$P\|h_{(win-flex-1)}\|\sum T_j$	Branch & Bound, GA
	Lei & Liu (2020)	$DR\|h_{(win-flex-m)}\|C_{\max}$	ABC
Age	Liao et al. (2007)	$P2\|r, h_{(pos-flex-m)}\|C_{\max}$	Branch & Bound, Heuristics
	Xu et al. (2008)	$P\|h_{(age-win-flex-m)}\|C_{\max}$	Approximation algorithm (2)
	Sun & Li (2010)	$P2\|h_{(age-flex-m)}\|\sum C_j$	Approximation algorithm $(1+2\sigma)$,SPT
	Costa et al. (2016)	$Q\|h_{(age-flex-m)}\|\sum T_j$	MILP, HGA
	Lee et al. (2018)	$Pm\|h_{(age-flex-m)}\|\sum T_j$	Branch & Bound
	Wong et al. (2013)	$P\|h_{(age-flex-m)}\|C_{\max}$	GA
PM Policy	Berrichi et al. (2009)	$P\|FR_{Exp}, Avb_{\max}\|C_{\max}$	GA
	Moradi & Zandieh (2010)	$P\|FR_{Exp}, Avb_{\max}\|C_{\max}$	GA
	Mirabedini & Iranmanesh (2014)	$P\|IM, FR_{Weibull}, Rlb_{\min}\|\mathcal{F}$	GA, PSO
	Berrichi et al. (2010)	$P\|FR_{Exp}, Avb_{\max}\|C_{\max}$	ACO
	Chen & Wang (2018)	$P\|FR_{Weibull}, Rlb_{\min}\|C_{\max}$	ACO, MILP
	Mokhtari et al. (2012)	$P\|FR_{Exp}, Avb_{\max}\|C_{\max}$	PVNS
Combination	Liao et al. (2017)	$P\|FR_{Weibull}, h_{(win-flex-m)}, RMA_{j-time}\|z(C_{\max}, \sum Cm_m)$	GA

by Wang & Wei (2011) by considering a different objective, which is the total machine completion time and total machine load. They show that both can be solved in polynomial time. Cheng et al. (2011) and Wang et al. (2014) extend Wang & Wei (2011) to the unrelated parallel machine environment. Cheng et al. (2011) show that each of their objectives can be solved in $O(n^{m+3})$ time if the processing time of a job after the RMA is less than its processing time before the RMA. The note by Yang et al. (2012c) on the study by Cheng et al. (2011) proves that the problem can be solved in $O(n^{m+3})$ time, no matter what the processing time of a job is with respect to the RMA. Ma et al. (2015b) and Ma et al. (2015a) study a similar maintenance problem as in Wang & Wei (2011) and introduce past-sequence-dependent delivery times.

Yang (2011), Yang, Cheng, Yang, & Hsu (2012a), Lee, Yang, & Yang (2013), Wang (2013), Abedi, Seidgar, & Fazlollahtabar (2017) study problems where the job processing time depends on the position in the sequence and for which an RMA is scheduled to restore the job deterioration. These studies show that their proposed problems can be solved in polynomial time, except for the study by Abedi et al. (2017), where a GA and an Imperialist Competitive Algorithm (ICA) is proposed. Yang (2011) examine both a power and linear dependent deterioration: $p_{jr} = p_j r^{a_j}$ and $p_{jr} = p_j + b_j r$ where r is the position in the sequence and a_j and b_j are deteriorating factors. They consider one RMA per machine. Lee et al. (2013) also consider one RMA per machine and study power position-dependent deterioration, i.e., $p_{ijr} = p_{ijr}^{a_j}$. Yang et al. (2012a) extend the study by Lee et al. (2013) to the case where multiple RMA's are scheduled per machine. In addition, they examine a linear position-dependent deterioration, i.e., $p_{ijr} = p_{ij}r$. A similar linear position-dependent deterioration is studied in

Abedi et al. (2017), though a different objective and solution method are proposed. A special type of position-dependent deterioration is considered by Wang (2013). Multiple RMA's per machine may be scheduled and an RMA is an imperfect PM activity, thereby dividing the jobs into multiple groups. The job processing time depends not only on the group it is scheduled in, but also on the position within that group.

Woo, Jung, & Kim (2017), Woo & Kim (2018) and Da, Feng, & Pan (2016) study the problem where the processing time of a job depends on the time elapsed since the last RMA. In Da et al. (2016), job processing time deteriorates linearly in time. The deteriorating factor is modeled through the machine age, which is defined according to a unique Weibull failure rate per machine. They consider minimal repair activities, replacements and PM activities, of which each incurs a different cost. The standard NSGA-II algorithm is applied to their problem. In Woo et al. (2017) and Woo & Kim (2018), job processing time depends linearly on the time since the last RMA. Both studies present an MILP and a GA for the problem. In addition, Woo & Kim (2018) also present an SA meta-heuristic solution and show that the SA outperforms their GA and the GA by Woo et al. (2017) on a set of publicly available data. Linear time deterioration is also studied in Xu, Yin, & Li (2010) and Grigoriu & Briskorn (2017), though it is not the job processing time that deteriorates, but the maintenance duration. In Xu et al. (2010), maintenance is scheduled similarly as in Xu, Sun, & Li (2008), i.e., the time between two consecutive maintenance activities is within the interval $[T_1, T_2]$. The time required to perform PM is an increasing linear time-dependent function of the total processing time of the jobs that are processed after its last maintenance. Grigoriu & Briskorn (2017), on the other hand, consider a maintenance level (ML) per machine, which can vary continuously between a minimum and maximum. Each job has a unique deteriorating factor which reduces the ML. A PM restores the ML to its maximum level and the duration depends on the difference between the current ML to its maximum. Both Xu et al. (2010) and Grigoriu & Briskorn (2017) provide approximation algorithms for these problems.

In Chan, Chung, Chan, Finke, & Tiwari (2006b), Chan, Chung, & Chan (2006a), Chung, Lau, Lo, & Ip (2009), Tian, Yu, & Luo (2019) and Khalid & Yusof (2014), only the maintenance duration deteriorates. In the first four studies, maintenance duration depends on the age of the machine and is modeled through a hypothetical maintenance scheme. For example, between ages A and B, maintenance takes $X + Zt$ hours, but between ages B and C, maintenance lasts $Y + Qt$ hours, where t is the time since the last maintenance. Each machine has a maximum age and perfect PM must be scheduled before reaching this age. Chung et al. (2009) consider maintenance to be perfect or imperfect. In addition, they incorporate a hazard rate that reduces the reliability of the machine. The reliability should be kept above a specified threshold. Tian et al. (2019) present a similar maintenance scheduling problem as Yu & Seif (2016). For the identical parallel machine environment, they consider multiple ML's for each machine represented by a non-negative integer value. Each job has a specific deterioration rate. Maintenance can be performed during any ML and restores the machine to any level. The duration of maintenance depends on the current ML and the level to which it is restored. The authors present an ILP. In Khalid & Yusof (2014), a linear relationship exists between the maintenance duration and the machine age, where duration equals three times the machine age. There is a maximum age and, when it is exceeded, maintenance must be performed. The authors study a distributed flexible manufacturing system, similar to Chan et al. (2006b), Chan et al. (2006a) and Chung et al. (2009). An AIS is developed by Khalid & Yusof (2014), while Chan et al. (2006b), Chan et al. (2006a) and Chung et al. (2009) propose a GA to solve the problem.

A combination of time or position-dependent deterioration of job processing time and maintenance duration is studied in Hsu, Ji, Guo, & Yang (2013), Yang (2013), Gara-Ali, Finke, & Espinouse (2016), Wang & Li (2018), Lu, Liu, Pei, T. Thai, & M. Pardalos (2018), Zhang, Wu, Lin, & Wu (2018) and Poongothai, Godhandaraman, & Anitha (2019). In Hsu et al. (2013), only one RMA is scheduled per machine and three types of deteriorating effects for jobs are considered: (1) job-dependent aging, (2) linear time-dependent aging and (3) position-dependent aging. In addition, the duration of the deteriorating maintenance activity is a linear function of its starting time. Yang (2013) extends on Hsu et al. (2013) by considering multiple RMA's per machine. Similarly, the maintenance duration is modeled as a function of its starting time. For job deterioration, a combined job and position-dependent and linear time-dependent deterioration is proposed, $p_{ijr} = p_j f_{ij}(r)$ and $p_{ijr} = p_{ij} + \delta_i t_{ir}$, respectively, where $f_{ij}(r)$ is the deteriorating factor of job j scheduled in the rth position on machine i, δ_i is a common deteriorating factor of jobs processed on machine i and t_{ir} is the starting time of a job processed in the rth position on machine i. Gara-Ali et al. (2016) consider a deteriorating maintenance activity with a duration that depends on the time elapsed since the last maintenance, while the job processing time depends on its position in the schedule. Linear time-dependent maintenance deterioration and position-dependent job deterioration are also studied by Zhang et al. (2018). Though, they extend the study by Gara-Ali et al. (2016) by allowing a maximum number of RMA's per machine. Wang & Li (2018) study the similar maintenance deterioration as in Gara-Ali et al. (2016), but linear time-dependent job deterioration is considered. Similarly, in Lu et al. (2018), both job processing time and maintenance time depend on their starting time with respect to the last maintenance. They are the first to propose a meta-heuristic solution for this unrelated parallel machine scheduling problem type. Poongothai et al. (2019) consider both position-dependent and time-dependent job deterioration. Polynomial solvable solutions are provided by Hsu et al. (2013), Yang (2013), Gara-Ali et al. (2016), Wang & Li (2018) and Zhang et al. (2018), while Poongothai et al. (2019) propose an MIP. Lu et al. (2018) are the only to provide meta-heuristic solutions: a Hybrid ABC and a TS.

4.2.2. Scheduling in a flexible window

In the work of Lee, Wang, & Lee (2015), maintenance is scheduled in a flexible window on parallel machines. For each machine, one maintenance activity must be scheduled. The authors develop a B&B algorithm and a GA. A useful lower bound is proposed and instances up to 20 jobs are solved to optimality. A distributed unrelated parallel machine scheduling problem is studied by Lei & Liu (2020). Multiple maintenance activities per machine are considered and each maintenance activity is scheduled in a predefined flexible interval. They present an Artificial Bee Colony (ABC) algorithm with division (DABC). The DABC algorithm is compared to other meta-heuristics from literature such as a GA and a hybrid PSO with a GA. Computational results show that the DABC performs better for almost all problem instances.

4.2.3. Scheduling before reaching machine age

The studies by Liao, Chen, & Lin (2007), Xu et al. (2008), Sun & Li (2010), Costa, Cappadonna, & Fichera (2016), Lee, Kim, & Lee (2018) and Wong, Chan, & Chung (2013) schedule maintenance before reaching a certain age. All studies consider the problem where the consecutive time between two maintenance activities cannot exceed a certain threshold. The only exception is the work of Liao et al. (2007), where a fixed number of jobs between two consecutive maintenance activities is considered, similar to Yang, Hsu, & Kuo (2008). Xu et al. (2008) examine a special case of the problem. Maintenance activities with almost periodic time windows are considered. This indicates that the time between any two consecutive maintenance activities is within the interval $[T_1, T_2]$. In Wong et al. (2013), multiple maintenance activities are considered, each of which has a different age threshold. They show that jointly scheduling production and maintenance is more effective than a more rigid maximum age approach. Xu et al. (2008) and Sun & Li (2010) present polynomial approximation algorithms and provide worst-case bounds for their problems. Liao et al. (2007) and Lee et al. (2018) propose a B&B algorithm and provide optimal solutions to problem instances created by the authors. Costa et al. (2016) and Wong et al. (2013) present an HGA and GA, respectively. Costa et al. (2016) show that their HGA is superior compared against an SA and a classic GA on a benchmark of small-sized test problems.

4.2.4. Scheduling with a PM policy

The studies by Berrichi et al. (2009), Berrichi, Yalaoui, Amodeo, & Mezghiche (2010), Moradi & Zandieh (2010), Mokhtari et al. (2012), Mirabedini & Iranmanesh (2014) and Chen & Wang (2018) consider integrated scheduling of production and maintenance with a PM policy. Where Ruiz et al. (2007) consider a PM policy to maximize availability of each machine separately, Berrichi et al. (2009) is the first to consider system availability as a whole. System availability is included in the objective function. The authors propose to first generate a job schedule, followed by insertion of maintenance activities. A new criterion is introduced, referred to as the rational strategy. In this strategy, let S_j and C_j be the starting and completion time of job j and T_e is the expected time to perform PM. If $C_j - T_e \geq T_e - S_j$, then PM is advanced to S_j, otherwise it is performed at C_j. They propose a GA for the problem. Berrichi et al. (2010), Moradi & Zandieh (2010) and Mokhtari et al. (2012) extend on the problem of Berrichi et al. (2009) by presenting different meta-heuristic solutions. The ACO in the study by Berrichi et al. (2010) outperforms the GA presented earlier in Berrichi et al. (2009). Mirabedini & Iranmanesh (2014) and Chen & Wang (2018) consider the problem where maintenance is scheduled based on the reliability level of each machine. Mirabedini & Iranmanesh (2014) consider two thresholds and both perfect and imperfect PM. If the reliability is between the two thresholds, minimal repair can be performed. If the reliability falls below the lowest threshold, a full repair should be performed and the reliability of the machine is fully restored. Chen & Wang (2018) only consider one reliability threshold that cannot be exceeded. The studies by Mirabedini & Iranmanesh (2014) and Chen & Wang (2018) consider a Weibull time-to-failure distribution. All studies present meta-heuristic approaches and Chen & Wang (2018) also introduce an MILP. Among the meta-heuristics, GA and ACO are most common. Mirabedini & Iranmanesh (2014) and Mokhtari et al. (2012) also present a PSO and PVNS algorithm, respectively. All algorithms are specifically designed for the problems addressed.

4.2.5. Special cases

In the study by Liao, Chen, & Yang (2017), multiple characteristics of the problem types discussed in the previous sections are combined. The job processing times deteriorate and an RMA can restore this deterioration. The RMA may only be scheduled in a specified flexible time window. Furthermore, each machine has a health index H_k. Once it reaches H_{safe}, maintenance must be performed, but can only be scheduled in the time window. The time-to-failure is modeled by a Weibull distribution and when the machine reaches health index H_{fail}, the machine must be replaced. The job processing time is modeled as $p_i = p_{i0} + \alpha_i \times (1 - H_k)$. A GA is presented for this problem.

4.2.6. Discussion

The most intensively studied area of integrated maintenance and production scheduling is scheduling of an RMA on parallel machines. The problem by Zhao et al. (2009) was at the time of writing the catalyst for a gigantic stream of follow-up studies on similar problems. Many of the follow-up studies extend the initial problem by Zhao et al. (2009) by considering a different machine environment or objective function. Interestingly, in the early years polynomial time algorithms were the most common solution. The studies by Chan et al. (2006b) and Chan et al. (2006a) stood out as they were the first and one of the few during the early years to use a meta-heuristic (GA) for the RMA problem. Only recently, more meta-heuristic solutions have been adopted for these problems. Almost all combinations of RMA constraints have been studied on parallel machines; time-, position- and job-dependent deterioration as well as deterioration on maintenance duration and job processing time. Among the many studies emerging in this area, a notable study is the one by Yang (2013) that proposes combinations of multiple RMA constraints. Despite the wide variety of problems, a lack of benchmarking between the studies is observed. A major opportunity would be to develop meta-heuristic solutions for the problems treated in the early years and, at the same time, to benchmark these solutions. To that end, it would also be relevant to introduce real-life case-studies to estimate the potential benefit of the proposed solutions on factory practices.

Literature on scheduling maintenance in a flexible window is scarce. It seems that this stream of research has yet to emerge, as the only two studies currently considered are published recently. On the other hand, as will be featured later, for the combination of maintenance and resources, more research is performed on the parallel machines environment. Though, it would make sense to expand research in this area first, before moving to more complex situations.

Studies on scheduling maintenance before it reaches a certain age consider different environments, objective functions and constraints. The study by Wong et al. (2013) can be considered as state-of-the- art in this category as they extend the standard problem to multiple maintenance activities with varying thresholds. They are also the first to use GA as a solution method. Due to the variety of problems in this category, direct comparison is not possible. Therefore more research on similar problems is required to enable benchmarking. Another opportunity would be to study combinations of constraints similar to the ones in job shop and flow shop environments (the latter will be featured in the next section).

In the next section on flow-shop scheduling, it will be shown that the pioneering study by Ruiz et al. (2007) is the catalyst for research in the area of scheduling with a PM policy. An important extension of their work is the study by Berrichi et al. (2009), which considers the availability of the whole system, instead of each machine separately. This objective received significant follow-up within all machine environments. Although most studies consider similar environments and objective functions, slight differences in the constraints make them incomparable. Consequently, benchmarking is neglected at the moment. Since different solution methods have already been developed for a variety of problems, comparison of these methods is necessary to fill this gap. The most important opportunity in this category is to conduct more research which includes a benchmark.

4.3. (Flexible) flow shop

This section considers a flow shop environment and divides maintenance scheduling into the categories ‘Scheduling with an RMA’ (4.3.1), ‘Scheduling in a flexible window’ (4.3.2), ‘Scheduling before reaching machine age’ (4.3.3), ‘Scheduling with a PM policy’

Table 9
(Flexible) flow shop scheduling with maintenance.

Maintenance Type	References	$\alpha\|\beta\|\gamma$ Notation	Approach
RMA	Kubzin & Strusevich (2005)	$F2\|No-wait, RMA_{m-time-1-1}\|C_{\max}$	GA, TS
	Kubzin & Strusevich (2006)	$F2\|RMA_{m-time-1-1}\|C_{\max}$	Pseudopolynomial solvable
	Cheng et al. (2018)	$F\|RMA_{m-time}\|\sum C_j, T_{\max}, L_{\max}$	Polynomial Solvable $O(n^2m)$
	Huang & Yu (2016)	$F2\|RMA_{m-pos}\|C_{\max}$	ACO, CPSO
	Rudek & Rudek (2012)	$F2\|RMA_{j-pos}\|C_{\max}$	B&B, NEH, SA
	Gara-Ali & Espinouse (2015)	$F2\|RMA_{j-pos}, RMA_{m-time}\|C_{\max}$	B&B
	Seif et al. (2018)	$F\|RMA_{j-time}\|z(\sum T_j, \sum CM_m)$	Fuzzy LP
	Assia et al. (2020)	$F2\|ST_{sd}, RMA_{j-time}\|z(C_{\max}, \sum CM_m)$	MILP
Window	Aggoune (2003)	$F\|h_{(win-flex-m)}\|C_{\max}$	GA, TS
	Kaabi et al. (2004)	$F\|h_{(win-flex-m)}\|z(\sum T_j, \sum T_m, \sum E_m)$	GA
	Besbes et al. (2010)	$HF\|h_{(win-flex-1)}\|C_{\max}$	GA
	Luo et al. (2011)	$HF2\|h_{(win-flex-m-2)}\|C_{\max}$	GA
	Benbouzid-Si Tayeb et al. (2011)	$F\|h_{(win-flex-m)}\|z(C_{\max}, \sum T_m, \sum E_m)$	GA, TS, heuristic
	Boudjelida (2019)	$F\|r_j, d_j, h_{(win-flex-m)}\|z(C_{\max}, \sum T_m, \sum E_m)$	GA, TS, ACO
	Allaoui et al. (2008)	$F2\|nr, h_{(win-flex-1)}\|C_{\max}$	Prove NP-hardness
	Gara-Ali & Espinouse (2014)	$F2\|nr, h_{(win-flex-1)}\|C_{\max}$	Polynomial Solvable $O(n^2m)$
	Hadda (2015)	$F2\|nr, h_{(win-flex-1)}\|C_{\max}$	Polynomial Solvable
	Mosheiov et al. (2018)	$F2\|h_{(win-flex-1-2)}\|C_{\max}$	Approximation algorithm (1.5)
	Nouri et al. (2013)	$F\|RL, r_j, d_j, h_{(win-flex-m)}\|z(\sum CT_j, \sum CT_m)$	Heuristic
	Benbouzid-Si Tayeb & Belkaaloul (2014)	$F\|h_{(win-flex-m)}\|z(C_{\max}, \sum T_m, \sum E_m)$	AIS
	Chansombat et al. (2019)	$AF\|r_j, d_j, h_{(win-flex-m)}\|\sum CT_j$	MILP
Age	Yang et al. (2008)	$F2\|h_{(pos-flex-m)}\|C_{\max}$	Polynomial Solvable
	Cui et al. (2016)	$F\|h_{(age-flex-m)}\|C_{\max}$	MIP, HGA
	Lee & Kim (2017)	$F2\|h_{(age-flex-m-1)}\|\sum T_j$	MILP
	Xing et al. (2019)	$F\|h_{(age-flex-m)}\|z(C_{\max}, \sum TE_j)$	MILP, GA, HGA
	Feng et al. (2019)	$FF\|h_{(age-flex-m)}\|C_{\max}$	MILP, GA, PSO
	Yu & Seif (2016)	$F\|h_{(age-job-flex-m)}\|z(\sum T_j, \sum CM_m)$	MILP, GA
	Jung et al. (2018)	$F2\|h_{(age-job-flex-m)}\|C_{\max}$	MILP, GA, HS
PM Policy	Ruiz et al. (2007)	$F\|FR_{Weibull}, Rlb_{\min}, Avb_{\max}\|C_{\max}$	GA, SA, ACO
	Jabbarizadeh et al. (2009)	$FF\|ST_{sd}, FR_{Weibull}, Rlb_{\min}, Avb_{\max}\|C_{\max}$	GA, SA, SPT, LPT, Johnson rule
	Naderi et al. (2011)	$FF\|ST_{sd}, FR_{Weibull}, Rlb_{\min}, Avb_{\max}\|C_{\max}$	GA, AIS, SPT, LPT, NEH, Johnson rule
	Seidgar et al. (2016)	$AF2\|FR_{Exp}\|z(C_{\max}, Avb_{\max})$	GA, ICA
	Naderi et al. (2009b)	$FF\|ST_{sd}, FR_{Weibull}, Rlb_{\min}, Avb_{\max}\|C_{\max}$	VNS
	Miyata et al. (2019a)	$F\|no-wait, FR_{Weibull}, Rlb_{\min}\|\sum C_j$	Heuristic
	Wang & Liu (2014)	$FF2\|ST_{sd}, FR_{Exp}\|z(C_{\max}, Avb_{\max})$	TS
	Khatami & Zegordi (2017)	$FF\|ST_{sd}, FR_{Exp}\|z(C_{\max}, Avb_{\max})$	MILP, ACO
Combination	Miyata et al. (2019a)	$F\|ST_{sd}, FR_{Weibull}, RMA_{m-pos}, Rlb_{\min}\|C_{\max}$	Heuristic

(4.3.4) and some special combinations (4.3.5). An overview of the considered literature is provided in Table 9.

4.3.1. Scheduling with an RMA

The work of Kubzin & Strusevich (2005), Kubzin & Strusevich (2006), Cheng, Ying, Chen, & Lin (2018), Huang & Yu (2016), Rudek & Rudek (2012), Seif, Yu, & Rahmanniyay (2018), Assia, El Abbassi, El Barkany, Darcherif, & El Biyaali (2020) and Gara-Ali & Espinouse (2015) study the scheduling of production with an RMA. Kubzin & Strusevich (2005), Kubzin & Strusevich (2006), Cheng et al. (2018) and Huang & Yu (2016) consider a maintenance activity, the duration of which is deteriorating, while Rudek & Rudek (2012), Seif et al. (2018) and Assia et al. (2020) examine the case where job processing times are deteriorating. Gara-Ali & Espinouse (2015) consider both deteriorating processing times and maintenance durations. In all studies, RMA restores the processing time back to normal. Linear time-dependent deterioration is examined in the work of Kubzin & Strusevich (2005), Kubzin & Strusevich (2006), Cheng et al. (2018), Seif et al. (2018) and Assia et al. (2020) whereas the other studies consider position-dependent deterioration. In Gara-Ali & Espinouse (2015), position-dependent deterioration is examined for jobs while linear time-dependent deterioration is considered for maintenance. The studies by Rudek & Rudek (2012), Assia et al. (2020) and Gara-Ali & Espinouse (2015) present a mathematical formulation in the form of a B&B algorithm, while Kubzin & Strusevich (2005) and Kubzin & Strusevich (2006) provide polynomial time approximations. Huang & Yu (2016) and Rudek & Rudek (2012) and Seif et al. (2018) are the only studies that present meta-heuristic solutions. The SA by Rudek & Rudek (2012) cannot be compared to the ACO and CPSO developed by Huang & Yu (2016), since Huang & Yu (2016) considers deteriorating maintenance duration while Rudek & Rudek (2012) focuses on deterioration of job processing times. Seif et al. (2018) propose a GA-inspired algorithm which they name ALG and show that the ALG outperforms a standard GA.

4.3.2. Scheduling in a flexible window

Aggoune (2003), Kaabi, Varnier, & Zerhouni (2004), Allaoui, Lamouri, Artiba, & E.Aghezzaf (2008), Gara-Ali & Espinouse (2014), Hadda (2015), Mosheiov et al. (2018), Besbes, Teghem, & Loukil (2010), Luo, Huang, Zhang, & Dai (2011), Benbouzid-Si Tayeb, Guebli, Bessadi, Varnier, & Zerhouni (2011), Nouri, Fattahi, & Ramezanian (2013), Benbouzid-Si Tayeb & Belkaaloul (2014), Boudjelida (2019) and Chansombat, Pongcharoen, & Hicks (2019) consider scheduling PM in a flexible window. Most studies use strict flexible windows, but in the studies by Kaabi et al. (2004), Benbouzid-Si Tayeb et al. (2011), Nouri et al. (2013), Benbouzid-Si Tayeb & Belkaaloul (2014) and Boudjelida (2019), maintenance may be delayed or advanced beyond the time window, imposing earliness and tardiness penalties on the objective function. In all studies, the problem of multiple maintenance activities per machine is examined, except for the studies by Allaoui et al. (2008), Mosheiov et al. (2018) and Besbes et al. (2010), which allow only one activity per machine. Also, in the studies by Mosheiov et al. (2018) and Luo et al. (2011), maintenance is only performed on the second machine. Allaoui et al. (2008) provide a proof for the NP-hardness of their problem, which is then disputed by Gara-Ali & Espinouse (2014). They prove that the NP-hardness claim is false and provide a polynomial time algorithm to solve this problem. Hadda (2015) also show that some of the results of Allaoui et al. (2008)

are false. An approximation algorithm is presented in the work of Mosheiov et al. (2018), while mathematical formulations and mathematical programming solutions are presented by Nouri et al. (2013) and Chansombat et al. (2019). All other papers propose a GA for the problems, except for the study by Benbouzid-Si Tayeb & Belkaaloul (2014) which develops an AIS. In addition, Aggoune (2003), Benbouzid-Si Tayeb et al. (2011) and Boudjelida (2019) also propose a TS and Boudjelida (2019) develops an ACO as well. The TS outperforms the GA only in the study of Aggoune (2003), whereas the ACO achieves better results than both GA and TS in Boudjelida (2019). The studies of Aggoune (2003), Besbes et al. (2010) and Benbouzid-Si Tayeb et al. (2011) compare fixed maintenance with scheduling maintenance in a flexible window. Each study shows that flexibly scheduling maintenance results in better schedules. Benbouzid-Si Tayeb et al. (2011) and Boudjelida (2019) both examine a sequential and integrated approach for scheduling maintenance and jobs. They conclude that the integrated approach yields better results.

4.3.3. Scheduling before reaching machine age

The studies by Yang et al. (2008), Lee & Kim (2017), Cui, Lu, Zhou, & Han (2016), Xing, Qiao, & Lu (2019), Feng, Tan, Xia, Pan, & Xi (2019), Yu & Seif (2016) and Jung, Woo, Koh, & Kim (2018) consider scheduling maintenance before reaching a certain machine age. In Yang et al. (2008), maintenance is performed before reaching a limit on the consecutive number of produced jobs. The other studies, on the contrary, define a limit for the machine age in terms of time. In such case, maintenance can be started at any time unless the cumulative working time after the end of the previous maintenance exceeds a certain limit. The studies by Yu & Seif (2016) and Jung et al. (2018) examine a maintenance problem where each job deteriorates the machine at a different rate. Yu & Seif (2016) consider multiple ML which are reached through the deterioration of the jobs. Maintenance in each ML has a different cost and restores the machine to the best ML. Jung et al. (2018) on the other hand consider maintenance that must be scheduled before reaching a threshold which is reached through the job degradation. Cui et al. (2016) examine two variants for the age threshold: (1) idle time is included in the cumulative working time and (2) idle time is not included. Mathematical formulations are derived and mathematical programming models are provided in all studies except for Yang et al. (2008), that instead presents polynomial solvable solutions to a set of problem instances. Also, meta-heuristic solutions are provided in Cui et al. (2016), Xing et al. (2019), Feng et al. (2019), Yu & Seif (2016) and Jung et al. (2018). All studies, except for Cui et al. (2016) and Yu & Seif (2016), provide both a GA and an additional meta-heuristic solution, where both algorithms are compared. The HGA by Xing et al. (2019) and the Harmony Search (HS) algorithm by Jung et al. (2018) prove better than the standard GA.

4.3.4. Scheduling with a PM policy

In the work of Ruiz et al. (2007), Jabbarizadeh, Zandieh, & Talebi (2009), Naderi, Zandieh, & Fatemi Ghomi (2009b), Naderi, Zandieh, & Aminnayeri (2011), Miyata, Nagano, & Gupta (2019b), Wang & Liu (2014), Khatami & Zegordi (2017) and Seidgar, Zandieh, & Mahdavi (2016), maintenance is scheduled according to a policy. The study by Ruiz et al. (2007) is the first to introduce the scheduling problem where the interval of the maintenance activities is determined preparatory to scheduling the jobs. In their work, they first present three common policies from the literature to determine the PM interval: (1) policy I: preventive maintenance at fixed predefined time intervals, (2) policy II: optimum period model for the preventive maintenance maximizing the machines availability and (3) policy III: maintaining a minimum reliability threshold for a given production period t. Then, jobs and maintenance activities are scheduled simultaneously. Maintenance is scheduled according to the conservative criterion as mentioned in Section 4.1.4. Jabbarizadeh et al. (2009), Naderi et al. (2009b), Naderi et al. (2011) and Miyata et al. (2019b) extend the work of Ruiz et al. (2007) and adopt similar policies and approaches in their work. Wang & Liu (2014), Khatami & Zegordi (2017) and Seidgar et al. (2016) adopt the maintenance scheduling policy proposed by Berrichi et al. (2009), where instead of maximizing the machine availability, the whole system availability is considered. In these studies, failure rate is exponential and system availability is part of the objective function. Wang & Liu (2014) and Khatami & Zegordi (2017) schedule maintenance and production simultaneously, while Seidgar et al. (2016) apply an insertion strategy. In this strategy, first a job schedule is generated during each iteration and then maintenance is inserted according to the rational strategy proposed by Berrichi et al. (2009). All studies present meta-heuristic solutions, except for Miyata et al. (2019b), which presents multiple constructive heuristics. Khatami & Zegordi (2017) propose a mathematical model for their problem. A GA is presented in the studies by Ruiz et al. (2007), Jabbarizadeh et al. (2009), Naderi et al. (2011) and Seidgar et al. (2016). Each of these studies also propose a different meta-heuristic solution or heuristics, to compare with GA. In all studies, GA is outperformed by the other meta-heuristics. Ruiz et al. (2007) show that ACO performs better compared to GA and SA, while in Jabbarizadeh et al. (2009), SA outperforms GA. In Naderi et al. (2011), the proposed AIS also outperforms GA, and the ICA developed in Seidgar et al. (2016) proves to be better than a standard NSGA-II. A reason for outperformance of GA is that often a standard GA is adopted for comparison to a tailor-made meta-heuristic.

4.3.5. Special cases (Combination)

In the study by Miyata, Nagano, & Gupta (2019a), a problem is addressed which combines aspects from both the study of Ruiz et al. (2007) and Yu & Seif (2016). Each job deteriorates the machine and as a result, a machine has different ML's where the duration of maintenance depends on the current ML of the machine. There is a minimum ML which cannot be exceeded and maintenance restores the ML to its maximum level. A machine is also subject to failures where the time-to-failure is modeled by a Weibull distribution. The third policy of Ruiz et al. (2007) is adopted, i.e., a minimum reliability is ensured throughout the scheduling horizon. First a job schedule is generated and maintenance is inserted afterwards, according to a criterion which sequentially evaluates the position of a PM on all possible positions in the schedule. A mathematical model and some constructive heuristics are presented. The heuristics are evaluated through computational experiments on a set of small and large sized instances.

4.3.6. Discussion

Studies on scheduling with an RMA are scattered due to the diverse RMA problems and the different objective functions. This shows a wide variety of problems in this research area. Among these studies, the work by Rudek & Rudek (2012) is both the first to consider more than one RMA on multiple machines as well as the first to apply a metaheuristic (SA) solution. A novel element for the flow shop is the combination of deterioration for both jobs and maintenance in the study by Gara-Ali & Espinouse (2015). A major opportunity would be to study problems that consider the job-dependent deterioration constraint, as this is not yet studied despite the large diversity of problems. In addition, there is a major lack of benchmarking. Consequently, it is difficult to establish problem complexity and the best possible solution method to a specific problem. To fill these gaps, it is necessary to apply different solution methods for the present problems.

Literature on scheduling maintenance in a flexible window has been extensively studied. Both strict intervals as well as intervals that consider earliness and tardiness penalties are examined. In addition, a wide variety of objective functions is studied and both the cases of one and multiple maintenance activities per machine are analyzed. A frequently adopted solution method is GA. Though, whether this is the most appropriate solution method is questionable. Since, apart from the studies of Allaoui et al. (2008), Gara-Ali & Espinouse (2014) and Hadda (2015), no follow-up or benchmarking between studies is performed. Also, current research only considers one flexible window for maintenance, while the setting with multiple flexible windows for one maintenance activity has not yet been studied. The absence of these items provides opportunities for future research.

Research that considers scheduling maintenance before it reaches a certain age is not studied as extensively as the other maintenance types. A main novelty in this category is the scheduling of maintenance before the age-threshold, where the threshold is determined by job-dependent deterioration, as in the studies by Yu & Seif (2016) and Jung et al. (2018). Currently, proper benchmarking between studies and solution methods is missing. An opportunity for this research area would be to apply different solution methods for the existing problems and to compare them to the current solution methods.

The maintenance problem on scheduling with a PM policy has received serious attention. The pioneering study by Ruiz et al. (2007) has been significantly extended by other studies in this area. The work in Ruiz et al. (2007) laid the ground-work for extensions such as maximization of the whole system availability by Berrichi et al. (2009). Combinations of constraints, machine environments and objective functions are studied, providing a good overview of possible applications. Some studies perform benchmarking by comparing their solution method to a standard algorithm from literature (e.g. NSGA-II), whereas no comparison is performed on solution methods from studies in the field. Benchmarking by means of the latter approach is necessary to establish the most suitable solution method for a specific problem.

4.4. Takeaways; integrated production and maintenance scheduling

The main takeaways of the survey on the integrated scheduling of production and maintenance are summarized below.

- Parallel machines and flow shops are studied more often than job shops and open shops.
- The category of scheduling with an RMA is overwhelmingly studied for parallel machines.
- The category of scheduling in a flexible window is studied most in job shops and flow shop environments.
- Polynomial time algorithms are developed most often for parallel machines in the category of scheduling with an RMA.
- Meta-heuristic solutions are applied in the majority of studies for all categories and machine environments, except for the category of scheduling with an RMA.
- Objective functions on the completion time such as $C_{\max}$ and $\sum C_j$ are studied more than other types of objectives.
- Multi-objective problems are studied more in a job/open shop environment.
- Most of the studies consider self-contained problems, i.e., the problem that is studied is different from other problems in the related field. This is observed in terms of either machine environment, problem-specific constraints, solution approach or objective function. It means that almost all studies do not perform an explicit benchmark on one another. Studies exist that are identical in every aspect, but for which no benchmark is conducted.
- Scheduling before reaching a machine age on a job shop is considered in two studies only. Whereas the number of studies that consider scheduling with a PM policy is distributed approximately equally between the machine environments.
- Mathematical programming models such as ILP's or MILP's are provided occasionally. However, for flow shops that consider scheduling before reaching a machine age, almost all studies present a mathematical formulation of their problem.
- Occasionally, problems are extended to different machine environments by others. Sometimes, the differences in machine environment are small, e.g. extending a parallel machine problem to an unrelated parallel machine problem. However, the studies by Ruiz et al. (2007) and Berrichi et al. (2009), which are the first to consider scheduling with a PM policy, are frequently extended to other machine environments as well.

5. Resources and maintenance

In this section, literature regarding the integrated production, maintenance and resource scheduling problem is considered. The section is not divided into sections for each machine environment separately, as literature within some environments is scarce.

The study by Lee & Chen (2000) is the first to study the integrated maintenance and production scheduling problem, subject to resource constraints. Each machine must be maintained exactly once with a constant maintenance duration t within the time interval $[0, T]$, where $T \geq t$. Both unlimited and limited resource availability cases are examined. In the case of limited available resources, only one machine can be maintained at any given time. A B&B algorithm is presented for the problem and computational experiments on instances with up to 40 jobs show small integrality gaps, indicating good solutions within a reasonable time. A similar problem for a flexible job shop environment is addressed by Wang & Yu (2010). In their case, at least one maintenance activity takes place on each machine and in the case of limited resources, at most one machine can be maintained at any given time. The starting time of maintenance is within a predefined time window. For the multi-objective problem, a Filtered Beam Search (FBS) algorithm is presented and experiments show that better solutions are obtained for the case of unlimited resources. The study by Lee & Chen (2000) is also extended in the work of Yoo & Lee (2016). Similarly, at most one maintenance activity is scheduled per machine and in the case of limited resource availability, at most one PM can occur at any given time. They establish the complexity for each of the problem objectives. Also in the work of Rebai, Kacem, & Adjallah (2013), at most one maintenance activity can take place at a time and it can be scheduled anywhere along the scheduling horizon. Every machine is maintained once. Each maintenance activity features a tardy weight, early weight, optimistic and pessimistic deadline, respectively denoted by t_k^m e_k^m d_{k1}, d_{k2}. When the activity is performed between the optimistic and pessimistic deadline, the maintenance cost is minimal. Otherwise, early or tardy weights are imposed and the cost increases linearly with the starting time of the activity, i.e., $e_k^m(d_{k1} - t_k) + C_{k0}^m$ and $t_k^m(t_k - d_{k2}) + C_{k0}^m$ where t_k is the starting time of maintenance activity k. An MILP, a heuristic solution and GA are presented for the problem. A new maintenance problem that includes flexible windows for maintenance is addressed in the work of Geurtsen, Adan, & Adan (2020). In their study, a single maintenance activity holds multiple flexible windows, i.e., each maintenance activity can be scheduled in either one of its multiple windows. Multiple maintenance activities per machine are considered and the maximum number of maintenance activities that can be scheduled simultaneously is limited to the maximum number of available resources at that time. In this study, resources are technicians that are required to execute maintenance. The maximum number of technicians is limited and constant throughout the planning horizon. The maintenance scheduling aspect of this problem is novel as it has not been addressed in any literature in the category 'Scheduling in a flexible window'. An ILP is presented for the problem. For larger sized problem instances, a hybrid GA is developed. A case-study on real-world production data shows the efficiency of scheduling maintenance flexibly, compared to fixed maintenance.

The study by Tavana, Zarook, & Santos-Arteaga (2015) is the first to consider the combination of scheduling an RMA and resources for the unrelated parallel machine environment. The resource problem is described as a repairmen selection problem, i.e., to decide who of the repairmen is going to maintain which machine at what time. Each machine is maintained by only one repairman whereas each repairman can take care of more than one machine. The processing time of a job is subject to linear position-dependent deterioration, modeled by $p_{ijr} = p_{ij} + \alpha_{ij} r_j$ where α_{ij} is the deteriorating factor of job j on machine i and r_j is the position of the job. Multiple maintenance activities per machine may be scheduled and each RMA restores the machine to its original state. For the problem, a multi-objective ILP is presented. Additionally, a three-stage solution approach is presented for the problem. The first stage uses a fuzzy approach for repairmen selection. In the second stage, the multi-objective problem is converted to a bi-objective problem. In the third stage, goal programming is applied and the optimal positions and the frequencies of the maintenance activities are determined. Simultaneous consideration of deteriorating jobs and resource constraints is also addressed for the flow shop environment in the study by Aramon Bajestani & Beck (2015). A finite planning horizon is considered, which is composed of K discrete time periods, each T time units long. Resources are modeled as highly skilled maintenance technicians required to perform PM, of which there is a constant limited availability C during each discrete time period. Every machine has a set of states $\{0, 1, \ldots, S_m\}$ where the current state s_m of the machine is defined by the number of time periods since the last maintenance activity. In state s_m, the machine speed is defined as $v^m_{s_m}$ and maintenance restores the speed back to its original speed v^m_0. The processing of a job is modeled as $p_{mj} = \frac{n_{mj}}{v^m_{s_m}} b_{mj} + \frac{n_{mj}}{v^m_0}(1 - b_{mj})$ where n_{mj} is the processing time of job j at $s_m = 0$ and b_{mj} is 0 if job j is processed after the maintenance activity in period k and 1 otherwise. The total number of machines that can be maintained in each period is limited to the number of available resources C. An MILP is developed for the problem and they show that the integrated approach yields better results than the non-integrated approach.

Not only maintenance workers may function as resource in an integrated maintenance, resource and production scheduling problem, but resources which are required during production, such as a mould for a machine, can also act as resource. In the study by Wong, Chan, & Chung (2012), a specific mould is required to produce a certain job on a machine. There is a limited number of moulds available for producing a specific type of job. In their work, both machines and moulds are subject to preventive maintenance. Similar to the work of Chan et al. (2006b) and Chung et al. (2009) in Section 4.2.1, for both the mould and the machine a hypothetical maintenance scheme is adopted. The maintenance duration is determined based on this scheme, including linear time relationships. Maintenance is perfect and must be performed before the maximum age of the machine or the mould. For this problem, a GA is developed based on the approach proposed by Chan et al. (2006b). Computational results show that jointly scheduling maintenance and production produces better results compared to no integration. Later, their work is extended in Wong, Chan, & Chung (2014) by considering a setup time for maintenance and precedence constraints between jobs. The idea behind this setup time is to avoid performing maintenance too early. A GA is developed and the simultaneous maintenance and production scheduling problem is compared to the problem where maintenance is performed just before the maximum machine age, i.e., without the rules of the scheme. Computational results show that the joint approach outperforms the maximum-age approach. The study by Wang & Liu (2015) also examines the job-mould assignment problem and consider partial flexibility where a job can only be processed by a subset of the available moulds. The type of mould that is used also changes the processing time of the job. Though, the processing time is independent of the machine on which the mould is placed. Both full flexibility (all moulds are eligible for the jobs) and partial flexibility cases are examined. In addition, both the mould and the machine require maintenance and the time to failure is modeled by an exponential distribution. A similar approach as studied by Berrichi et al. (2009) is adopted, i.e., the availability of the complete system is maximized, comprising both moulds and machines. Different to the work of Berrichi et al. (2009), maintenance activities are not inserted, but considered simultaneously with job scheduling. A multi-objective GA is presented and they show that the integrated method outperforms the method which considers periodic PM planning. It is also established that full flexibility of machines and moulds leads to better results. The study by Fu, Chan, Niu, Chung, & Qu (2019a) also addresses a problem where both machine and mould require maintenance. A job can only be allocated to a specific mould of which there is a limited available quantity, and a specific mould can be allocated to different machines but not all machines. Both require maintenance. The relationship between maintenance time and machine or mould age is described by a piece-wise linear function. A maintenance activity must be scheduled before reaching the maximum age and the maximum age of the mould is shorter than that of the machine. Perfect maintenance is considered. For the problem, a hybrid PSO is developed. The algorithm is benchmarked against the work presented by Wong et al. (2012). The maintenance scheme of the resources and three datasets are adopted. They show that their algorithm obtains better results, but also demonstrate that the running time explodes with increasing instance size. Fu, Chan, Niu, Chung, & Bi (2017) examine the job shop environment where both machine and mould require maintenance. The relation between mould and machine usage is similar as in Fu et al. (2019a). The duration of the mould and machine maintenance is modeled by means of a schema, similar as in Chan et al. (2006b), Chung et al. (2009) and Wong et al. (2012). A PSO and GA are presented and computational experiments on four different instances show better results for the PSO algorithm.

As mentioned in Section 2.2, literature dealing with non-renewable resources would not be considered in Section 3. However, two studies are found that examine the integrated production, maintenance and resource scheduling problem with non-renewable resources. Due to the scarcity of integrated production, maintenance and resource scheduling work, these two studies are included here. Liu & Wang (2016) study a problem involving deteriorating maintenance activities, deteriorating jobs, and non-renewable resource consumption. A linear resource consumption function is considered, modeled by $p_{ij} = \bar{p}_{ij} - a_{ij} u_{ij}$, $0 \leq u_{ij} \leq \bar{u}_{ij} < \frac{\bar{p}_{ij}}{a_{ij}}$ where $\bar{p}_{ij}$ represents the normal processing time, u_{ij} the number of allocated resources and $\bar{u}_{ij}$ the upper bound on the number of resources that can be allocated. Job processing time is further defined by a deterioration rate α_{ij} which is multiplied by the equation of the linear resource consumption. Each machine has at most one maintenance activity, the time of which deteriorates lin-

Table 10
Combined maintenance and resource scheduling.

Maintenance Type	References	$\alpha\vert\beta\vert\gamma$ Notation	Approach
Job Shop & Open Shop	Wang & Yu (2010)	$FJ\vert h_{(win-flex-m}, res111\vert z(C_{\max}, W_{\max}, \sum Wm_j)$	FBS
	Fu et al. (2017)	$P\vert RMA_{m-time}, res\cdot\cdot 1\vert C_{\max}$	PSO
Flow Shop	Aramon Bajestani & Beck (2015)	$F\vert d_j, RMA_{j-time-pos}, res1\cdot 1\vert \sum CM_m$	MILP
Parallel machines	Lee & Chen (2000)	$P\vert nr, h_{(win-flex-m-1)}, res111\vert \sum w_jC_j$	B&B
	Yoo & Lee (2016)	$P\vert h_{(flex-m-1)}, res111\vert \mathcal{F}$	Dynamic programming
	Rebai et al. (2013)	$R\vert h_{flex}, res111\vert z(\sum w_jC_j \sum TC_m, \sum EC_m)$	MILP, GA, heuristic
	Geurtsen et al. (2020)	$R\vert h_{(win-flex-m)}, res1\cdot 1\vert z(C_{\max}, \sum T_j)$	ILP, HGA
	Tavana et al. (2015)	$R\vert RMA_{j-time-pos}, res\cdot\cdot 1\vert \mathcal{F}$	ILP
	Belkaid et al. (2014)	$P\vert FR_{Exp}, res\cdot\cdot\cdot, Avb_{\max}\vert C_{\max}$	GA, MIP
	Wong et al. (2012)	$P\vert RMA_{m-time}, res\cdot\cdot 1\vert C_{\max}$	GA
	Wong et al. (2014)	$P\vert Prec, RMA_{m-time}, res\cdot\cdot 1\vert C_{\max}$	GA
	Wang & Liu (2015)	$P\vert FR_{Exp}, res\cdot\cdot 1, Bi, Avb_{\max}\vert C_{\max}$	GA
	Fu et al. (2019a)	$P\vert RMA_{m-time}, res\cdot\cdot 1\vert C_{\max}$	PSO
	Liu & Wang (2016)	$R\vert RMA_{j-time}, RMA_{m-time}, res\cdot\cdot\cdot, Lin\vert z(C_{\max}, \sum C_j, \sum \theta_j u_j)$	Polynomial Solvable

Table 11
Summary solution methodologies.

Problem type	Resource category	Maintenance category	Integrated category	Total
Heuristics	50	11	1	62
GA	13	38	6	57
Polynomial solvable	17	32	1	51
Approximation algorithms	13	8	-	21
MILP	2	17	2	21
MIP	11	2	1	14
NP-hard	12	-	-	12
ACO	3	7	-	10
SA	4	6	-	10
B&B	3	5	1	9
TS	3	6	-	9
PSO	2	3	2	7
AIS	1	5	-	6
CP	6	-	-	6
IP	5	-	-	5
VNS	2	3	-	5
ABC	-	3	-	3
Dynamic programming	2	-	1	3
FFO	3	-	-	3
LP	2	1	-	3
ILP	-	1	2	3
Machine Learning	3	-	-	3
MA	2	1	-	3
FBS	-	1	1	2
ICA	-	2	-	2
Lagrangian relaxation	2	-	-	2
NPM	2	-	-	2
ABCO	-	1	-	1
CPSO	-	1	-	1
DABC	-	1	-	1
DCRO	-	1	-	1
DNS	1	-	-	1
GRASP	-	1	-	1
HS	-	1	-	1
VDO	1	-	-	1

early as a function of its starting time. The first job immediately after the maintenance activity does not have deterioration. They show that the problem is solvable in polynomial time. The study by Belkaid, Dahane, Sair, & Khatab (2014) is somewhat similar to that of Wang & Liu (2015). They consider a parallel machine environment, where each job requires a specific set of components, which are modeled as consumable (non-renewable) resources. The components are procured by suppliers at different times throughout the scheduling horizon and represented by a curve in the form of stairs. In addition, for maintenance, the approach introduced by Berrichi et al. (2009) is adopted with the goal of maximizing the whole system availability. Maintenance activities are inserted according to the rational strategy proposed by Berrichi et al. (2009). An MIP is presented and a GA is developed for the integrated problem.

Studies that consider combined maintenance and resource scheduling activities are summarized in Table 10.

5.1. Discussion and takeaways; integrated production, maintenance and resource scheduling

In this section, no division by machine environment is performed, since, evidently, literature on the integrated scheduling of both maintenance and resources is scarce. This research area seems to be in its early stage. Although the first study on this topic appeared in 2000 by Lee & Chen (2000), it took ten more years for the next study in this area to appear, by Wang & Yu (2010). As just 12 studies have appeared since then, it seems like studying the integrated production, maintenance and resource scheduling problem has just started. Though, 8 out of those 12 studies have appeared in the last five years, indicating that research in this area is on the rise. Research in similar areas and machine environments, but without either resource constraints or maintenance constraints, has grown significantly in the past decade. Hence, it is logical to expect that research in this specific area will also grow in the near future. In particular, it would be interesting to study problems that are already widely studied in a variant without either resources or maintenance. Examples of studies considering only maintenance include: scheduling with a PM policy using either one of the solution methods proposed by Ruiz et al. (2007) or Berrichi et al. (2009), the RMA scheduling problem by Zhao et al. (2009) and its extensions or the standard problem of scheduling with a flexible window where more than one maintenance activity is considered, such as the studies by Aggoune (2003), Kaabi et al. (2004) or Benbouzid-Si Tayeb et al. (2011). In studies that only consider resources, it would be interesting to add maintenance activities to problems that consider labor flexibility and the learn-forget-learn model, such as in Fry et al. (1995) and Jaber & Neumann (2010).

Also, it is important for this research stream to get a better picture of the practical relevance. In order to achieve this, more collaboration with industry on real-life case studies is required to obtain insights on the impact of integrated production, maintenance and resource scheduling.

The main takeaways of the survey on the integrated scheduling of production, maintenance and resources are summarized below.

- Literature on the integrated scheduling of both maintenance and resources is scarce.
- Almost all studies examine the parallel machine environment.
- Speeding up resources is only considered in two studies, the rest focuses on static problems
- A few studies consider the problem of scheduling in a flexible window and the problem of scheduling with an RMA.
- Only one study examines the maintenance category of scheduling with a PM policy.
- The category of scheduling before reaching a machine age is not examined at all.
- Research on integrated scheduling of maintenance and resources is scattered. Each study examines a new problem that differs from the other work in terms of objective function, constraints or solution method. An exception is the study by Fu et al. (2019a) who perform a benchmark against the work of Wong et al. (2012).
- The work by Geurtsen et al. (2020) is the only study that collaborates with industry to provide a real-life problem with real production data.

6. Conclusions

Due to the competitiveness of today's global markets, companies have to become more efficient when creating schedules at the operational level. Increasing productivity, reducing the number of non-added value activities and improving the effective use of resources needed during production play a pivotal role. This requires the concurrent scheduling of maintenance activities, resources and production in order to both reduce machine idle times and increase total productivity. This review paper addresses the problem where classical production scheduling is extended with either resources, maintenance or a combination of both, and where the problem remains deterministic. This review surveys 236 papers in total with 110, 112, 14 papers for each of the aforementioned categories, respectively. A majority of the scheduling problems in real life situations involve both the addition of resources and maintenance scheduling. Despite the fact that this survey does not cover the full extent of both constraints (non-renewable resources and single machine environments are not taken into account), there is already a lot more research to be done on this topic in general.

Considering only the addition of resources towards the scheduling problem, 45, 55 and 10 papers have been found in the job/open shop, parallel machine and flow shop environment, respectively. While the job/open shop and the parallel machine environment constitute approximately the same number of papers, flow shop environments have not been considered thoroughly, where it is also noticed that 6 of these studies are performed by the same author. More research on flow shop scheduling is therefore needed. Regarding the parallel machine environment, a larger portion of the studies considers a fixed resource effect, while speeding up effects are examined most often in a job shop environment. In contrast, it is observed that most research on job shop scheduling studies the DRC problem, i.e., considering workers as an extra constraint. Less literature is found on the addition of other resources that are required during the processing of a job. Thus more research is needed within this category.

While considering the addition of maintenance activities to the production scheduling problem, a different conclusion is drawn compared to resources. The field of parallel machines is investigated more intensively compared to both flow shops and job/open shops (53, 37 and 22, respectively). Hence, more research on job shop and flow shop environments is needed. Moreover, for the parallel machine environment, more research is required on the effect of scheduling maintenance in flexible time windows, whereas literature on scheduling with an RMA and scheduling before reaching a machine age is scarce for the job shop environment.

In the job shop and flow shop category for the integrated resource scheduling problem, many identical problems are studied, while the opposite is true for parallel machines and all categories within the integrated maintenance scheduling problem. Here, the studies are actually scattered and differ in either constraints, machine environment, solution approach or objective function. Although some researchers compare their results to others, in most cases no explicit benchmarking is performed, especially in the case of integrated maintenance scheduling. In integrated resource scheduling, studies are often very similar in nature, but unfortunately, researchers do not compare their results or provide benchmark cases for future studies. Comparison of solution methods for the same problem is required to identify the most effective approach.

The reviewed studies use a wide variety of solution methods. The summary of occurrences of each solution method is provided in Table 11. First, it must be noted that the type of solution methods differs significantly per category. Heuristic methods are most common in scheduling with additional resources, while GA and polynomial solvable methods are popular in the maintenance scheduling problems. Overall, heuristics, GAs and polynomial solvable methods are the most dominant approaches. When looking deeper into the differences between the environments, one may find that the majority of polynomial solvable methods within the maintenance category can be accounted to the parallel machine environment. Also notable is that within the job shops with additional resources, current literature emphasizes the use of different solution methods, whereas less focus is put on the comparison of effects of different problem characteristics (e.g. worker flexibility). Regarding the objective function, performance measures related to the completion time (e.g. $C_{\max}$, $\sum C_j$) are most often considered, whereas other objectives related to earliness, tardiness or costs are considered less and if they are considered, it is generally by means of a multi-objective approach. Although the completion time measure is usually related most directly to the performance of a company (i.e., on time delivery), other performance measures should also be investigated more thoroughly and independently, as these can also be beneficial for savings within a company.

Finally, limited studies consider the combination of production, resources and maintenance scheduling activities. This specific combination is not only interesting for academics, but also very relevant in practice. Studies on integrated scheduling have so far shown that improvements can be realized when maintenance and/or resources are considered in addition to production, when compared to production scheduling without consideration of maintenance and/or resources. Therefore, it is important to study the integration of operations such that industry can benefit as well. Most of the current studies that combine these three operations only consider parallel machines. Other machine environments should also be investigated more thoroughly. Furthermore, the absence of real world problems or problems that use real production data is noticed within the literature. Since the integrated production, maintenance and resource scheduling problem is a common problem in many real-live production environments, it is advised to conduct more collaborative research with industry using real data and solving actual problems.

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