Production planning and scheduling in multi-factory production networks: a systematic literature review

Jacob Lohmer*, Rainer Lasch

Technische Universität Dresden, Chair of Business Management, esp. Logistics, Münchner Platz 1-3, 01062 Dresden, Germany

jacob.lohmer@tu-dresden.de; rainer.lasch@tu-dresden.de

ORCiD: 0000-0002-3197-6159

Production planning and scheduling in multi-factory production networks: a systematic literature review

Multi-factory production planning and scheduling problems have been increasingly studied by scholars recently due to market uncertainty, technological trends like Industry 4.0 and increasing collaboration. Geographically dispersed factories may provide cost-saving potential and increase efficiency while also being subjected to varying capabilities and restrictions such as capacity constraints and labour costs**.** Traditional approaches in production planning and scheduling focus on the allocation of demand to a single factory and obtain sequences of operations on machines in this factory. In the multi-factory or distributed setting, an additional task includes assigning orders to potential factories beforehand. Starting with the first case studies in the late 1990s, research has increasingly been devoted to this research field and has considered numerous variations of the problem. We review 128 articles on multi-factory production planning and scheduling problems in this contribution and classify the literature according to shop configuration, network structure, objectives, and solution methods. Bibliometric analysis and network analysis are utilised to generate new findings. Research opportunities identified include integration with other planning stages, an investigation of key real-life objectives such as due date compliance and examining dynamic characteristics in the context of Industry 4.0. Besides, empirical studies are necessary to gain new practical insights.

Keywords: production planning, production scheduling, multi-factory, distributed scheduling, systematic literature review

1. Introduction

Companies manufacturing goods in the 21st century are faced with increasingly complex customer requirements, uncertain markets and customer expectations for fast product delivery (Mack et al. 2015; Bennett and Lemoine 2014). This has led to various efforts by manufacturing companies to meet customer requirements quickly and thus reduce production lead times (Kriett, Eirich, and Grunow 2017; An and Yan 2016)**.** Distribution of production capacity among several factories, which are, in many cases, geographically distributed, is increasingly used (Olhager and Feldmann 2018). Large companies have several production sites to which orders must be assigned in order to efficiently fulfil customer orders (H. K. Chan and Chung 2013; Ruiz, Pan, and Naderi 2019). Besides, small- and medium-sized companies work together collaboratively in production networks sharing capacities, leading to a similar situation (Hosseini and Tan 2019). Operating multiple factories may provide cost-saving potential and increase efficiency while also being subjected to varying capabilities, capacity constraints and labour costs. In addition to strategic decisions, production planning and scheduling is one of the biggest drivers to increase efficiency in the network and exploit the potential. Production planning and scheduling problems have been analysed and solved extensively in the past, but to a large extent only considered the traditional single factory configuration (Allahverdi et al. 2008; Blazewicz, Domschke, and Pesch 1996; Allahverdi 2015). After orders are assigned to be produced in a specific period according to customer demands or forecasts, scheduling deals with the allocation of determined resources to tasks over a set of time periods to optimise one or multiple objectives (Pinedo 2014).

In *multi-factory production planning and scheduling*, also synonymously referred to as *distributed production planning and scheduling*, there is an additional task involved: The assignment of jobs to available factories is succeeded by sequencing operations on machines. The crucial task here includes determining the optimal schedule of jobs in a production network so that technical, logistical, and timing constraints are met. The general multi-factory or distributed scheduling problem is illustrated in Fig. 1. The different shop configurations are explained in more detail in Section 3.2.

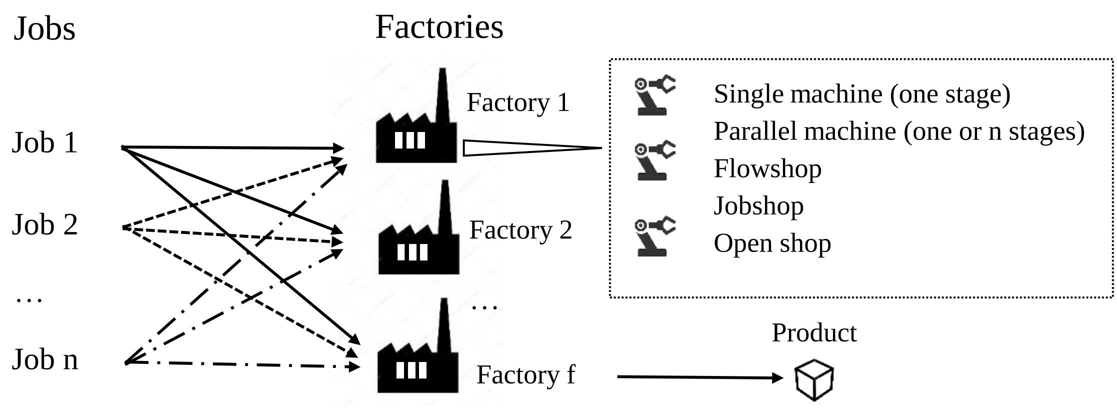

Figure 1. An illustrative example of multi-factory or distributed scheduling

Multi-factory production planning and scheduling has proven to be relevant in various areas as indicated by its application in practical settings in different sectors, such as semiconductor manufacturing (Azevedo and Sousa 2000; Wang, Yang, and Yu 2018), hardwood flooring (Gascon, Lefrançois, and Cloutier 1998), the automotive industry (Gnoni et al. 2003; Cicirello and Smith 2004), the pharmaceutical industry (Miller and De Matta 2003; De Matta and Miller 2004), the concrete industry (Naso et al. 2007; Garcia, Lozano, and Canca 2004), TFT-LCD manufacturing (Lin and Chen 2007; Tsai and Wang 2009; Chen, Huang, and Lai 2009; Chen 2014), the textile industry (Guo et al. 2015; Aissani et al. 2012; Kerkhove and Vanhoucke 2014) or PVC pipe production (Lei et al. 2019). As these studies show, many industries benefit from geographically separated factories and different wage levels. Scheduling is also relevant to industries with multiple factories in the same region, as time-to-market is critical and insufficient allocation to factories at the regional level can still have a significant impact on meeting due dates and securing follow-up business. Although research is also increasingly devoted to the topic at hand, no comprehensive review has been conducted yet to examine the complexity of the problem and current trends, to identify significant objective functions and solution methods, and to suggest meaningful directions for further research. The most recent review is narrative and covers articles up to the year 2013 (Behnamian and Fatemi Ghomi

2016). Due to the rapidly increasing number of publications on production scheduling, however, there is a need for up-to-date surveys of specific problem classes, such as the multi-factory case (Allahverdi et al. 2008). Therefore, in this paper, we provide a systematic and comprehensive review of multi-factory production planning and scheduling approaches and indicate further research potential. To the best of our knowledge, this is the first attempt to provide a systematic overview of scientific approaches and guide researchers and managers towards an efficient implementation of respective solution methods. Within this context, we attempt to answer the following research questions:

- RQ1: What distinguishes the multi-factory planning problem from a single-level planning problem? What are the current trends in research and what specific problems are being considered?
- RQ2: Which objectives have been studied and which solution methods have been used to solve multi-factory production planning and scheduling problems?
- RQ3: Which complexities of the problem remain unexplored and what future research directions can be recognised?

The rest of this paper is structured as follows: In Section 2, we briefly discuss the need for multi-factory production planning and scheduling and clarify the methodology of this literature review. Section 3 provides the analysis of multi-factory production planning and scheduling literature, specific features of the proposed models, typical constraints and assumptions, before the classification of the literature is presented. In this section, we answer RQ1 before we focus on the specific objectives and solution methods in Section 4 to answer RQ2. In Section 5, we provide directions for future research and managerial implications to answer RQ3. Then, we conclude the paper with a summary of our findings in Section 6.

2. Multi-factory production planning and scheduling – research approach

2.1 Need for multi-factory production planning and scheduling approaches

Production planning and scheduling are essential tasks in the administration and on the shop floor of every manufacturing company. The historically established models and approaches to production planning have focused on optimising the production planning and scheduling of a single factory. Today, single factories are often no longer able to react appropriately to uncertain market conditions, complex customer requirements, small order sizes and the need for shortened lead times (Mack et al. 2015; Bennett and Lemoine 2014). Single factories also pose severe risks for the welfare of companies (e.g. machine failures, governmental regulation, and environmental disaster). These threats and the new trends in the context of Industry 4.0 have led to fundamental structural changes in the manufacturing industry in recent years. Many companies have changed their production framework from a single factory setting to a multi-factory supply chain with geographically dispersed facilities (Chan, Chung, and Chan 2005; Moon et al. 2006; Lei et al. 2019). The benefits of these configurations are mainly the closer proximity to customers, the ability to produce products effectively for local market needs, short response times to changing market demand, and economic reasons such as transport cost or labour cost savings (Jia et al. 2003; Kanyalkar and Adil 2005; Jason, Liang, and Mak 2006; Chan et al. 2006; Ying and Lin 2018).

The resulting distributed production network is built upon coordination, collaboration, and synchronisation between the factories. The main issue is the coordination of production plans of several individual factories in such a way that the overall performance and competitive position of the company are considerably improved

(Bhatnagar, Chandra, and Goyal 1993). The improved technical feasibility of advanced algorithms has mainly led to an increase of importance for planning and scheduling orders in the multi-factory environment in the last two decades. Initially, articles often focused on exact solution methods to optimally solve the respective problem formulations. Despite stronger computational resources, only small to medium-sized problems can be solved by exact methods in a reasonable time today (Wu et al. 2017; Ying and Lin 2018). Literature reviews or overviews on this subject were contributed by Bhatnagar, Chandra, and Goyal (1993), Alvarez (2007), Chan and Chung (2013) and Behnamian and Fatemi Ghomi (2016). The latter considered articles until 2013 and included distributed single factory scheduling in a non-systematic, narrative review. Recent promising model formulations and meta-heuristics for distributed scheduling are missing in these reviews. Besides, the focus of the existing reviews varies considerably and the clarity of the methodological description can be criticised (Thomé, Scavarda, and Scavarda 2016; Tranfield, Denyer, and Smart 2003). To overcome the shortcomings in prior research, this paper presents a systematic and up-to-date literature review of production planning and scheduling approaches for multi-factory production networks.

2.2 Research methodology – systematic literature review

The design of this study follows Tranfield, Denyer, and Smart (2003) and Thomé, Scavarda, and Scavarda (2016) in conducting a systematic, explicit, and reproducible literature review. The systematic approach towards literature reviews has become increasingly popular in Operations Management studies and enables scholars to progress the current state-of-the-art in the area of interest (Thomé, Scavarda, and Scavarda 2016; Tranfield, Denyer, and Smart 2003). The systematic procedure is vital to minimise bias and ensure rigour and relevance of findings and research opportunities identified (Durach, Kembro, and Wieland 2017; Tranfield, Denyer, and Smart 2003; Fink 2013). According to Thomé, Scavarda, and Scavarda (2016), eight steps with corresponding clarifications are vital for a systematic literature review: planning and formulating the problem, literature search process, data gathering, quality evaluation, data analysis and synthesis, interpretation, result presentation, and review updating. We will deal with the specific elements of our procedure in the following.

2.2.1 Planning the review

The research team consisted of both authors, which participated in coding, synthesising and reporting of the results. The need for this review was indicated in Section 2.1, with the research questions specified in the introduction. Following Vom Brocke et al. (2009) and Cooper (1988), we define the *focus* of our study as assessing research outcomes, research methods and investigated applications in the field of multi-factory production planning and scheduling. The *goal* is an integrative synthesis of existing literature while also identifying critical issues. We try to maintain a neutral *perspective*, although this is considered difficult to achieve (Cooper 1988). Regarding *coverage*, we aim to be as comprehensive and exhaustive as possible and provide the details concerning our search process, inclusion as well as exclusion criteria below. *Organisation* is a fifth characteristic to distinguish reviews (Cooper 1988). Most scheduling reviews use a historical approach, introducing the topics in chronological order to highlight the developments and trends in the literature. We have decided on a different approach and treat the topic methodologically. After an overview of the literature set, we analyse features, constraints, shop configurations, input data, network structure and then dedicate a separate section to two important features, namely objectives and solution methods. However, to enable the reader to benefit from a historical analysis as well, we provide an Appendix with a detailed analysis of the literature in each shop configuration in a historical manner.

Finally, the *audience* of our article are scholars and interested practitioners, as the topic is of high relevance to the modern globalised manufacturing industry.

2.2.2 Conducting the review

The search for literature was conducted in March and repeated in June 2019 to include the most recent contributions. After a pilot test with different search strings (Thomé, Scavarda, and Scavarda 2016), we were able to narrow down the search thematically and defined the keywords for our study as depicted in Fig. 2.

First keyword		**Second keyword**
multi-factory OR multi-plant OR distributed OR integrated	**AND**	production planning OR production scheduling OR shop scheduling

Figure 2. Keywords for the systematic literature review

Search databases included *ScienceDirect* (Abstract, title or keywords), *Web of Science* (All Fields), *Business Source Complete (EBSCOhost)* (Abstract or title) and *Google Scholar*. This search returned 2,488 articles after removing duplicates, which were filtered according to practical and methodological screening criteria that are depicted in Table 1. The flowchart of the synthesis of the literature to obtain a comprehensive data set is illustrated in Figure 3. We only considered English-language articles in peer-reviewed journals, conference proceedings or books and excluded dissertations, unpublished articles, working papers and articles without peer review (Durach, Kembro, and Wieland 2017). Thus, 52 articles were excluded at the first stage. A time criterion for inclusion or exclusion was not used as we intend to provide a comprehensive review of all research efforts to date. The focus of this review is on centralised algorithms for multi-factory production planning and scheduling. We use the terms *multi-factory* and *distributed* interchangeably for networks of multiple facilities. However, we differentiate from the term *distributed computing* or *distributed scheduling* in the area of computer science (Toptal and Sabuncuoglu 2010). Several recent studies attempted global optimisation in the context of Industry 4.0 applying dynamic scheduling methods (Ouelhadj and Petrovic 2009; Leng and Jiang 2019) or decentralised methods in self-organisation (Leng, Jiang, et al. 2019). Others presented hybrids of these models, utilising new technologies like blockchain for smart manufacturing (Leng, Yan, et al. 2019; Lohmer 2019; Dolgui et al. 2020). Due to the high complexity of multi-factory networks, these subjects have not yet been interconnected. Most contributions referring to Industry 4.0 focus on single factories and rather isolated digitisation solutions concerning IoT capabilities, cloud computing and cyber-physical systems (Rossit, Tohmé, and Frutos 2019; Ivanov, Dolgui, and Sokolov 2019; Parente et al. 2020). Some authors use the term *integrated* to indicate the joint consideration of production planning and scheduling. The term was considered in the search, but we excluded articles that primarily focus on integrating other related problems, such as integrated planning of lot sizing and scheduling or scheduling and distribution (refer to Chen 2010 or Copil et al. 2017).

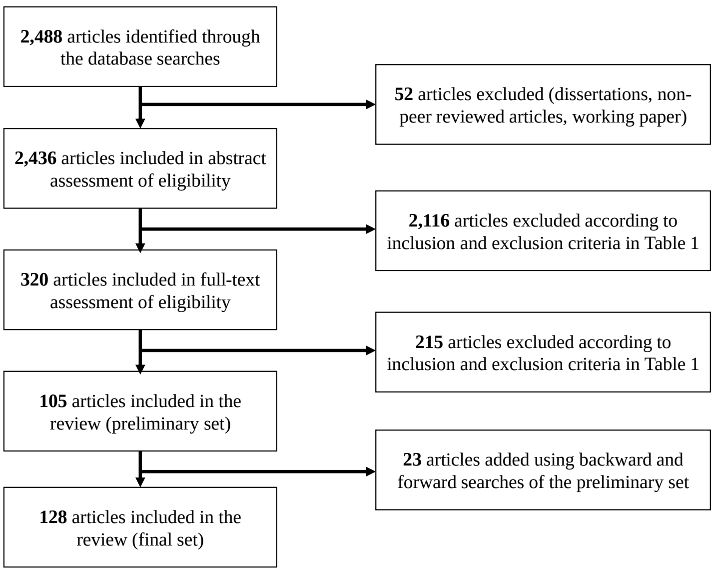

Figure 3. Flowchart of the review synthesis

The abstracts of the 2,436 remaining articles were assessed, taking into account all the mentioned criteria of Table 1 simultaneously. By only considering articles with a mathematical formulation and/or algorithms as quantitative solution methods and by excluding empirical papers as well as articles focused on decentralised methods or integrated problems, we accordingly selected 320 remaining articles for the next stage of full-text review. Full-text review is perceived as a crucial step in achieving a meaningful sample for the review (Thomé, Scavarda, and Scavarda 2016; Tranfield, Denyer, and Smart 2003; Vom Brocke et al. 2009). The full texts of the 320 articles were analysed in-depth, which further reduced the literature set to 105 relevant articles. This further reduction was mainly due to the fact that many authors use the same terminology for other types of problems, which only became apparent in the full-text analysis. Besides, several articles lacked an actual scheduling of orders, although this was referred to in the abstract. Next, we used the listed references and bibliographic details of the articles to extend our data set in snowball searches (backward and forward search) to be comprehensive in the specified research area and discover articles that use different terms for the same topic for various reasons. This resulted in 23 articles being added, leading us to our final set of 128 articles, which can be assessed in Section 3.6. The rather small number of additional articles through the snowball search indicates the validity of the research approach, the used keywords and databases.

Table 1. Inclusion and exclusion criteria for the literature review

	Rationale
Inclusion criteria	
Publication in peer-reviewed journals, conference proceedings or books	Peer-review is essential to guarantee a high quality of articles processed (Thomé, Scavarda, and Scavarda 2016)
Articles that present a mathematical formulation and/or algorithms to plan production and also schedule allocated jobs in the factories	Our focus is distinctively on production planning and scheduling. Articles dealing with only one of the areas have been disregarded, as well as articles that only present concepts for integration and problem solving
Quantitative papers rather than qualitative or empirical papers	Our focus is on quantitative papers. Case studies were only included if they present a mathematical model or algorithms applied in the industry
Exclusion criteria	

Articles that apply decentralised planning or scheduling algorithms	To differentiate from articles focusing on coordination methods, we excluded articles that use distributed computing capacities to solve tasks rather than a distributed, geographically dispersed production in multiple factories.
Articles focusing on integrated problems	There is a multitude of specific problems that can be solved in an integrated way, which is outside the scope of this review.

After the abstraction of information from the articles, the findings were synthesised descriptively and statistically (Thomé, Scavarda, and Scavarda 2016). In this contribution, we intend to familiarise the reader with the development of research, current trends, and research gaps in the multi-factory production environment. A concept matrix (Vom Brocke et al. 2009) was utilised to categorise and code the articles that included shop environment, factory type, demand structure, network structure, product flow, objective function, solution method, transportation characteristics, stochastic parameters and experiments. In a bibliometric analysis, we considered the frequency of publication, shop configuration, journal diversity, objective functions, solution methodology and more. In addition, we performed a network analysis to assess relevant developments of solution methodologies over time based on article keywords. Citation and co-citation were analysed to indicate important works in our literature set and co-authorships studied in terms of the collaborative spirit of the authors. This network analysis can be found in the Appendix 2 as supplementary material.

2.2.3 Dissemination over time and outlets

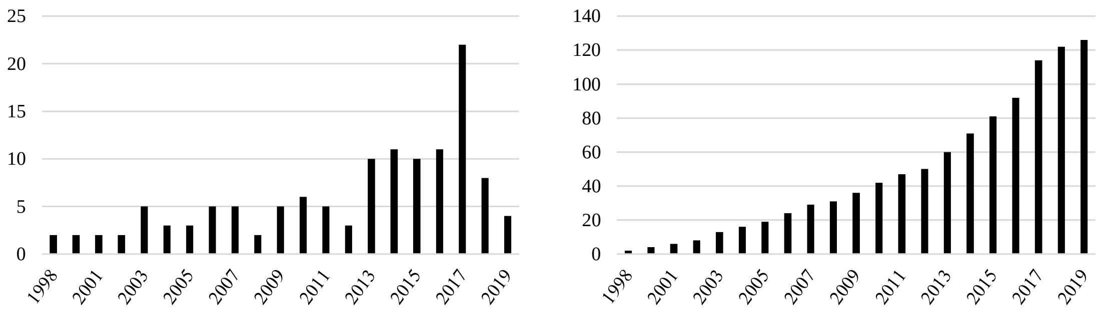

Figure 4. Number of publications per year and cumulative

The frequency of publications in the multi-factory or distributed environment is depicted in Fig. 4. At the beginning of research activities in the late 20th century, there were scattered publications. After the year 2013, the distributed problems gained increasing attention by researchers with a peak in 2017. This increased attention can be mainly attributed to the developments in computing, the advancement in meta-heuristics, and several benchmark instances made available publicly by different researchers (see Section 3.5.3).

The most relevant journals concerning the number of publications are displayed in Fig. 5. Majority of the research is published in *International Journal of Production Research, Computers & Industrial Engineering, Journal of Intelligent Manufacturing, International Journal of Production Economics and Expert Systems with Applications.* Conference proceedings accounted for 13 of the 128 publications (10%). In total, 53 different journals and conferences have published one or more articles in this field. This outlines the diversity of publishers and the interest from various research areas and streams.

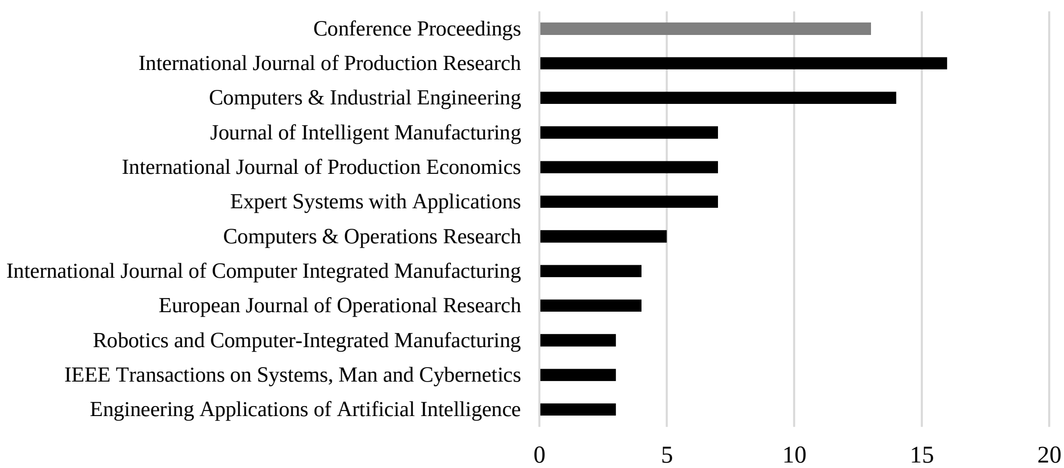

Figure 5. Publications per journal (journals with three or more publications only)

3. Analysis of multi-factory production planning and scheduling literature and classification

This section is focused on the analysis and classification of all identified articles according to shop configuration, factory types, demand type, type of network structure, objective function, solution method and model formulation (RQ1). After the introduction of the basic problem and its features, Section 3.2 analyses the different shop configurations and presents the identified subproblems. Section 3.3 then analyses the network configuration of the literature set, where homogeneous and heterogeneous factories can be distinguished. The complexity of the models is significantly influenced by the input data, which are also discussed here. Then, an analysis of the network structure follows in Section 3.4 before other characteristics are examined in Section 3.5 that were revealed by the analysis, including transportation between factories, stochastic parameters like machine unavailability and the use of benchmark instances. All publications on multi-factory production planning and scheduling analysed in this review are then summarised in Table 2 in Section 3.6, with the categorisation of the literature according to the presented criteria.

3.1 Basic problem, features and constraints

In multi-factory or distributed production planning and scheduling, the assignment of jobs to factories is succeeded by the task of sequencing operations on the machines: A set N of n jobs (representing customer orders or lots) have to be processed in a set G of f factories. Each factory has a set M of m machines that can be equal or different. The processing times $P_{j,i}$, $j \in N$, $i \in M$ are usually known in advance and deterministic, but can be stochastic as well (Naderi and Ruiz 2010). Each job j needs m operations which have to be performed in the same factory or in several factories. To represent the different variants of processing characteristics and configurations, the nomenclature proposed by Graham et al. (1979) and implemented by Pinedo (2014) can be used: In the three-field notation $\alpha/\beta/\gamma$, the first field, α, represents the shop configuration, β provides details on constraints and specific characteristics and γ indicates the objective function. α in the multi-factory case could be either single machine, parallel machine, flowshop, jobshop, or open shop (Behnamian and Fatemi Ghomi 2016). The possible entries for β and γ are detailed below.

In the basic formulation for a permutation flowshop by Naderi and Ruiz (2010), all jobs are available at time 0 and can be produced in all factories. Each machine can only process one job and a job can only be processed on one machine at a time; pre-emption is also prohibited. A job that is assigned to a factory for processing cannot be transferred to another factory. Binary and continuous variables are used frequently in models in the literature, e.g. $Y_{j,f} = 1$ indicates if job j is processed in factory f (0 otherwise), $C_{j,i}$ represents a continuous variable for the completion time of job j on the machine i. Most articles use these completion times to calculate (and minimise) the makespan $C_{max} = C_{\pi(n),m}$ with π as the permutation of jobs j. The traditional scheduling problem of assigning limited production resources to activities over time in a single factory can be classified as NP-hard (Garey and Johnson 1979). As multi-factory scheduling problems are reduced to their corresponding traditional scheduling problems if the number of factories is set to one, we can conclude that multi-factory scheduling problems in their different variants are also NP-hard (Bargaoui, Driss, and Ghédira 2017a; Wu et al. 2017).

3.2. Shop configuration

The publications are categorised according to their shop configuration, meaning the specific processing order of jobs and the available machine types on the shop floor in the factories. Similar to single factory scheduling, the multi-factory research stream has attracted research contributions in five main shop configurations (Pinedo 2014).

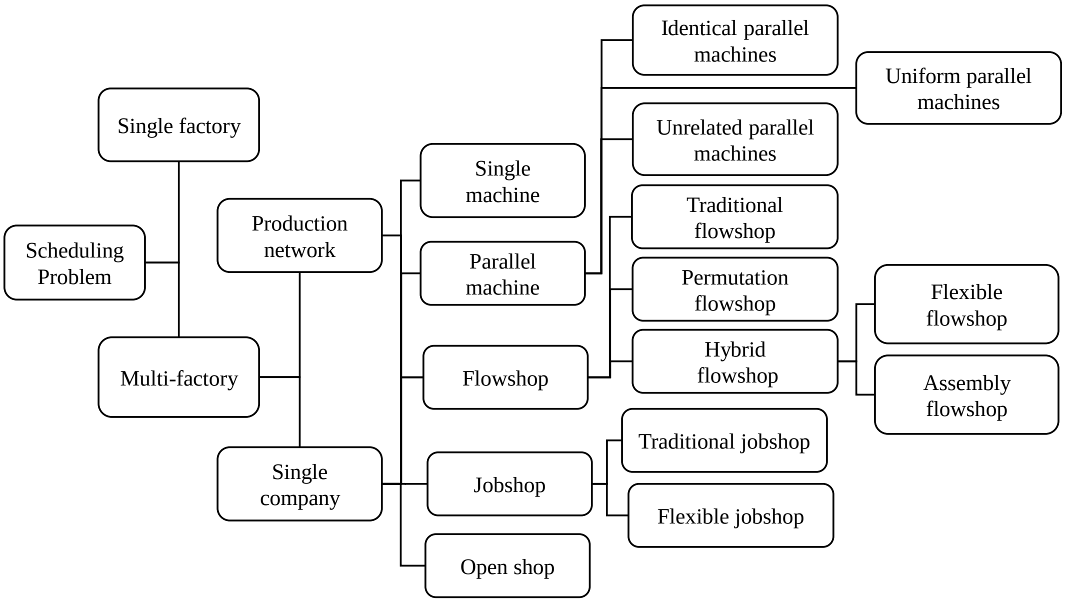

Figure 6. Classification of multi-factory scheduling problems (extended from Behnamian and Fatemi Ghomi 2016)

Fig. 6 illustrates the different configurations found in the literature, namely single machines in each factory, parallel machines, flowshop, jobshop or open shop configurations (please refer to the Appendix for detailed analysis of all identified shop configurations, specific characteristics and a breakdown of all assigned articles of the literature set). As the following paragraphs indicate, most of the literature is devoted to flowshop problems. The ratios are depicted in Fig. 7. Of the literature in our sample, 54 articles address multi-factory flowshops, followed by 42 articles that study jobshops. 18 articles deal with parallel machines, 12 with single machine settings and a further 2 articles on open shop scheduling were identified.

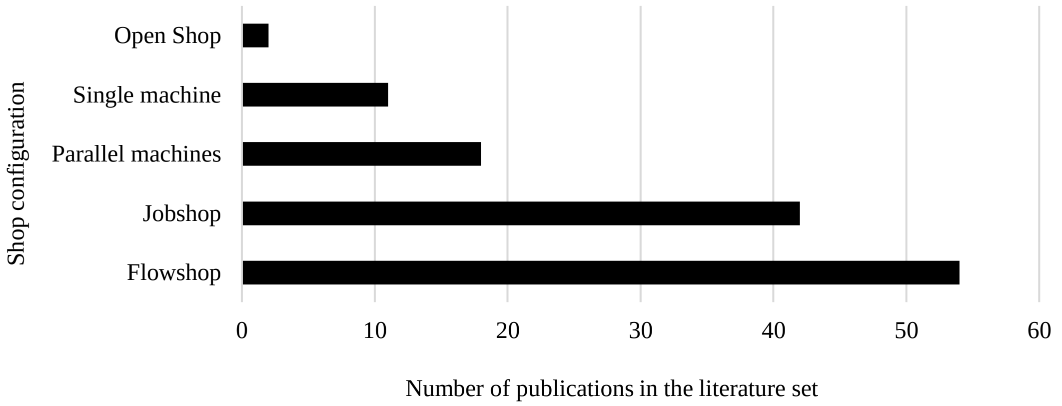

Figure 7. Publications per shop configuration

3.2.1 Single machine scheduling

Single machine (*SM*) scheduling problems have been the topic of extensive research since the seminal work by Jackson (1955) for single factory scheduling. Here, *n* jobs are assigned to *f* factories that each contain one machine or a single stage with aggregated machine capacities (Nigro et al. 2003; Naso et al. 2007; Chung, Chan, and Ip 2011; Marandi and Fatemi Ghomi 2019). Out of the 12 articles studying *SM* in the literature, 9 present mixed-integer linear problem formulations. Genetic algorithms and imperialistic competitive algorithms are most frequently applied.

3.2.2 Parallel machine scheduling

In parallel machine (*PM*) scheduling in the multi-factory case, there are *n* jobs that have to be assigned to *f* factories. All jobs have one single operation as in the case of single machine environments. Each factory f has m_f parallel machines and a job can be processed on any of the free machines (Kerkhove and Vanhoucke 2014). In total there are $W = \sum_{f=1}^{F} m_f$ machines. 14 of the 18 articles deal with heterogeneous factories. The machines in parallel may be identical, have different speeds (uniform), or may be completely unrelated (Allahverdi et al. 2008). Interestingly, the contributions in our literature set are often motivated by practical case studies, significantly more often than the other shop configurations (e.g. Cicirello and Smith 2004; Cóccola et al. 2013; Lei et al. 2019). 15 out of 18 articles dealing with *PM* present heuristics or meta-heuristics. Furthermore, the analysis shows a particular accumulation of multi-criteria objective functions for *PM* problems (also refer to Table 4 below).

3.2.3 Flowshop scheduling

The largest share of contributions deals with flowshops (*FS*): A flowshop consists of several stages with one or more machines at each stage, in an *m*-machine flowshop there are *m* stages in series (Allahverdi 2015). All jobs are processed in the same order. A permutation flowshop also limits the job sequence to one solution for all stages, in the multi-factory environment referred to as DPFSP (Naderi and Ruiz 2010). Moreover, there are flexible flowshops with more than one machine in at least one of the stages (Xu, Sand, and Engell 2010) and assembly flowshops with a first set of $k - 1$ operations in the first stage and the assembly operation *k* in a second stage, respectively. The *distributed assembly permutation flowshop scheduling problem* (DAPFSP) considers a set of *f* identical factories with *m* machines processing *n* jobs that are then assembled in a different single factory (Hatami, Ruiz, and Andrés-Romano 2013). The *two-stage* version (DTSAFSP) assumes that production and assembly can be located in a single factory, which is selected from a set of multiple factories (Xiong et al. 2014). When no in-process waiting is allowed, the *distributed no-wait flowshop* (DNFSP) is considered. Other variants of the DPFSP include the *distributed two-machine flowshop scheduling problem* (DTMFSP) (Deng, Wang, Shen, et al. 2016; Dempster, Li, and Drake 2017), hybrid flowshops (Hao et al. 2019), no-idle flowshops (Ying et al. 2017), blocking flowshops (DBFSP) without buffers between consecutive machines (Companys and Ribas 2016) and multi-processor tasks (Ying and Lin 2018). The flowshop setting is common in several industries, such as automotive or electronics manufacturing (Allahverdi et al.

2008). The literature on distributed flowshops has increased sharply since the introduction of the DPFSP by Naderi and Ruiz (2010) with 48 articles on one of the variants of the problem in the last decade. To include the different variants of flowshop problems in our analysis, the column on the far right of Table 2 indicates the specific problem variant considered in the article.

3.2.4 Jobshop scheduling

In a jobshop (*JS*) with *m* different machines, each job needs processing on machines in an individual routing. Some machines in the given route may be skipped, some repeated. Similar to flowshops, in a distributed flexible jobshop (DFJSP) more than one machine exists in at least one stage (Chan, Chung, and Chan 2005; De Giovanni and Pezzella 2010). The classic jobshop scheduling problem (JSP) has been studied since the 1950s in Operations Research (Jackson 1956). The distributed jobshop setting involves three decisions that increase complexity accordingly: factory assignment, operation assignment to machines, and operation sequencing on machines. More than 70% of JS articles present heuristics or meta-heuristics to solve the complex problem instances.

3.2.5 Open shop scheduling

Different from the other scheduling problems, in an open shop (*OS*) each job has to be processed once on each of the *m* machines, passing them in any order (Allahverdi et al. 2008). Only two articles study a distributed or multi-factory open shop scheduling problem: Jia et al. (2002) and Li and Ou (2007). The open shop configuration does not occur in as many industries as flowshop or jobshop configurations, as only particular products are manufactured in this manner.

3.3 Network configuration and input data

Network configuration has a significant impact on the problems under study and their complexity. Factories in the network can either be identical (homogenous) or heterogeneous, e.g. considering different machine configuration or varying processing times. 62 articles in our study use identical, homogeneous factories. This reduces the computation complexity and allows for more extensive use of additional capacity in the intra- or interorganisational network. Interestingly, the vast majority of articles with homogenous factories deal with flowshops (44 of 54 articles on *FS*). 66 articles deal with heterogeneous factories, where in most cases the process times on the machines vary for the individual operations. These instances are mainly found in *SM*, *PM* and *JS* configurations.

Model complexity is also influenced by demand as an input variable, which is static or dynamic and deterministic or stochastic. All order data is available at $t = 0$ in static settings, while for dynamic settings the demand changes with the elapse of time. Demand is deterministic when the occurrence and quantity is known reliably and distinctly, while stochastic demand uses possibility distributions to model uncertainty. Most articles deal with static and deterministic demand (85 of 128 articles), while the remainder focuses on dynamic and deterministic demand (19 of 128 articles). Stochastic demand is only considered in 24 articles (19% overall), with *JS* being examined the most comprehensively and diversely in this context (15 articles). The assumption of deterministic and/or static demand can be considered as unrealistic but is due to the complexity of the problem (Hatami et al. 2018). Future research efforts should nevertheless address this issue and include stochastic demand configurations which predominate in industry (Gonzalez-Neira et al. 2017).

3.4 Network structure

Network structure refers to the configuration of the underlying supply chain or production network: In parallel, the factories in the network compete on the same level. In most contributions, all the production operations for a job take place in one of the available factories (see Fig. 1). Serial production in a multi-factory network includes several stages and multiple factories for at least one stage, e.g. a single factory in stage 1 and three factories for stage 2. While for single machine settings the ratio is balanced (6 parallel, 6 serial), in the other cases a clear majority of parallel configurations is evident. For *PM* and *OS* there are no articles with serial configuration, while for *FS* and *JS* there are 6 articles each, amounting to 11% and 14%, respectively. As manufacturing networks are developing into multi-stage supply chain networks due to globalisation, digitalisation and Industry 4.0 trends (Ruiz, Pan, and Naderi 2019; Olhager and Feldmann 2018), increased research considering serial network structures is promising for future research efforts.

3.5 Other characteristics of multi-factory production planning and scheduling

3.5.1. Transportation

The consideration of several factories in production planning and scheduling is particularly useful when customers and markets are geographically dispersed. It may be profitable for capacity or cost reasons to manufacture products in a factory further away and accept a longer transportation route. However, more than half of all articles (71 articles) do not consider transportation in any way. When transportation is considered, it is mainly the transportation of finished goods to the customer or selling locations (e.g. Chen and Pundoor 2006; Tsai and Wang 2009; Karimi and Davoudpour 2017a; Marandi and Fatemi Ghomi 2019). Other options include transportation between machines in a factory or plant to plant (Moon, Kim, and Hur 2002; Chan, Kumar, and Mishra 2008), transportation between factories in a serial configuration (Thoney et al. 2002; Miller and De Matta 2003; De Matta and Miller 2004; Ruifeng and Subramaniam 2011; Sun, Chung, and Chan 2015) or transportation of raw material from an Input/Output centre to factories and finished goods back to the Input/Output centre (Kopanos and Puigjaner 2009; De

Giovanni and Pezzella 2010; Lu et al. 2015; Li et al. 2016; Chang and Liu 2017; Wu et al. 2017). Most studies are still based on the assumption that transportation during processing causes too much effort or has a negative effect on meeting delivery times.

3.5.2 Stochastic parameters

Maintenance or unavailability of machines in the context of stochasticity and dynamic scheduling is studied in several contributions. However, the overall number is rather small. 117 of 128 articles assume constantly available machines, steady processing times and job availability at time t = 0. Unexpected machine breakdowns are considered by Cicirello and Smith (2004) and Wang, Huang, and Qin (2016). A larger group of articles focused on expected and/or unexpected machine maintenance (Chan et al. 2006; Chan and Chung 2007; Chung, Chan, and Chan 2009; Chung et al. 2009; Ruifeng and Subramaniam 2011). Processing time uncertainty was also considered sporadically (Guo et al. 2015; Ji et al. 2016; Gonzalez-Neira et al. 2017; Hatami et al. 2018). For reasons of complexity, most authors assume that all resources are continuously available, although this is a rather unrealistic assumption that does not occur in industry.

3.5.3 Benchmark instances

To test and compare the effectiveness and efficiency of solution algorithms, benchmark instances are crucial. Several instances can be accessed for the different shop configurations: 540 instances for *PM* by Behnamian and Fatemi Ghomi (2013), 720 instances for the DPFSP by Naderi and Ruiz (2010) (available at http://soa.iti.es/), for the DAPFSP by Hatami, Ruiz, and Andrés-Romano (2015), and for the *JS* by De Giovanni and Pezzella (2010). Experiments based on real configurations are rare and conditions often simplified (e.g. Lei et al. 2019, Aissani et al. 2012. The analysis shows that there is still a need to develop benchmark instances for the different shop configurations that adequately reflect the diversity of real-world manufacturing systems.

3.6. Literature classification

Table 2 below categorises all identified literature on multi-factory production planning and scheduling. The literature is sorted chronologically for each shop configuration. An analysis of objectives and solution methods follows in the next section. More detailed descriptions of the individual articles with tables arranged according to the shop configurations can be found in Appendix 1 in historical order.

Table 2. An analysis of multi-factory production planning and scheduling literature

Author and year	Shop configura-tion	Factory type		Demand	Network structure		Objective	Solution method					Specific problem
		hom	het		serial	par		Exact	IP	Heuristic/Meta-heuristic	Sim.	Other	
Nigro et al. (2003)	SM		√	st, det		√	Cost, Service				√	MAS	
Garcia, Lozano, and Canca (2004)	SM	√		dyn, det		√	Profit	√	√	Heuristic			
Naso et al. (2007)	SM	√		dyn, det		√	Cost + M_{util}		√	Hybrid GA			
Tsai and Wang (2009)	SM		√	st, det	√	√	Profit		√				
Chung, Chan, and Ip (2011)	SM		√	st, det	√	√	$\sum T_j$			Hybrid GA			
Shah and Ierapetritou (2012)	SM	√		dyn, det		√	Cost	√	√				
Chen (2014)	SM		√	st, det	√		Profit		√		√		
Karimi and Davoudpour (2015)	SM		√	st, det	√		Cost	√		Heuristic			
Feng et al. (2017)	SM		√	st, det		√	Cost		√	Heuristic		NLP	
Karimi and Davoudpour (2017a)	SM		√	st, det	√		Cost		√	Heuristic		TIM	
Karimi and Davoudpour (2017b)	SM		√	st, det	√		Cost		√	ICA			
Marandi and Fatemi Ghomi (2019)	SM		√	st, det	√	√	Cost		√	ICA			
Gascon, Lefrançois, and Cloutier (1998)	PM	√		dyn, stoch		√	Inventory, Service			Heuristic	√		
Sauer (1998)	PM	√		dyn, det		√	M_{util}, $\sum Tj + \sum Ej$, Cost			Heuristic, GA			
Guinet (2001)	PM		√	st, det		√	$\sum Tj + \sum Ej$, Cost		√	Heuristic			
Cicirello and Smith (2004)	PM	√		dyn, stoch		√	Cost, C_{max}, Throughput				√		
Chen and Pundoor (2006)	PM		√	st, det		√	$\sum Cj$, Cost			Heuristic		Dyn. Pr.	
Almada-Lobo, Oliveira, and Carravilla (2008)	PM	√		st, det		√	Inventory, M_{setup}		√	VNS			
Terrazas-Moreno and Grossmann (2011)	PM		√	dyn, det		√	Profit	√	√				
Behnamian and Fatemi Ghomi (2012)	PM		√	dyn, det		√	C_{max}, $\sum Cj$		√	ICA		ε-constr. method	
Behnamian and Fatemi Ghomi (2013)	PM		√	st, det		√	C_{max}		√	Heuristic, GA + LS			
Cóccola et al. (2013)	PM		√	st, det		√	Cost	√	√				
Behnamian (2014)	PM		√	st, det		√	Cost + Profit		√	VNS + TS			
Kerkhove and Vanhoucke (2014)	PM		√	st, det		√	Cost (Tj)		√	Heuristic, GA + SA			
Behnamian (2015)	PM		√	st, det		√	Cost	√	√				
Yazdani, Gohari, and Naderi (2015)	PM		√	st, det		√	C_{max}, $\sum Cj$		√	ABC			
Behnamian (2016)	PM		√	st, det		√	C_{max}			Heuristic + PSO			
Behnamian (2017a)	PM		√	st, det		√	C_{max}		√	PSO			
Behnamian (2017b)	PM		√	st, det		√	Cost		√	Matheuristic			
Lei et al. (2019)	PM		√	st, det		√	C_{max}			ICA			DPMSP
Azevedo and Sousa (2000)	FS		√	st, det		√	$\sum Tj + \sum Ej$, Cost		√	SA			
Gnoni et al. (2003)	FS		√	dyn, stoch		√	Cost		√		√		
Miller and De Matta (2003)	FS		√	dyn, det		√	Cost		√				

Author and year	Shop configura-tion	Factory type		Demand	Network structure		Objective	Solution method					Specific problem
		hom	het		serial	par		Exact	IP	Heuristic/Meta-heuristic	Sim.	Other	
Lin and Chen (2007)	FS		√	dyn, det		√	Cost		√				
Chen et al. (2009)	FS	√		dyn, det		√	$\sum Tj + \sum Ej$, M_{util}, Inv.				√		
Xu et al. (2010)	FS		√	st, det		√	C_{max}, Inv.		√	Heuristic			
Naderi and Ruiz (2010)	FS	√		st, det		√	C_{max}		√	Heuristic			DPFSP
Liu and Gao (2010)	FS	√		st, det		√	C_{max}			EM			DPFSP
Ruifeng and Subramaniam (2011)	FS		√	st, det		√	Profit	√					
Gao and Chen (2011)	FS		√	st, det		√	C_{max}			GA + LS			DPFSP
Gao, Chen, and Deng (2013)	FS		√	st, det		√	C_{max}			TS			DPFSP
Lin, Ying, and Huang (2013)	FS		√	st, det		√	C_{max}			IGA			DPFSP
Hatami, Ruiz, and Andrés-Romano (2013)	FS	√		st, det		√	C_{max}		√	Heuristic			DAPFSP
Wang et al. (2013)	FS	√		st, det		√	C_{max}			EDA			DPFSP
Xu et al. (2014)	FS	√		st, det		√	C_{max}			IA + LS			DPFSP
Naderi and Ruiz (2014)	FS	√		st, det		√	C_{max}			SS			DPFSP
Xiong et al. (2014)	FS	√		st, det		√	$\sum C_j$			VNS, hybrid GA, hybrid DEA			DTSAFSP
Xiong and Xing (2014)	FS	√		st, det		√	C_{max}, $\sum C_j$		√	GA-RVNS			DTSAFSP
Hatami, Ruiz, and Andrés-Romano (2015)	FS	√		st, det		√	C_{max}		√	Heuristic, VND, IGA			DAPFSP
Fernandez-Viagas and Framinan (2015)	FS	√		st, det		√	C_{max}			BSIG			DPFSP
Li et al. (2015)	FS	√		st, det		√	C_{max}			GA			DAPFSP
Deng, Wang, Shen, et al. (2016)	FS	√		st, det		√	C_{max}			HS			DTMFSP
Lin and Ying (2016)	FS	√		st, det		√	C_{max}		√	ICG			DNFSP
Deng et al. (2016)	FS	√		st, det		√	C_{max}		√	MA			DTSAFSP
Wang, Huang, and Qin (2016)	FS	√		st, det		√	C_{max}			EDA, GA			DPFSP
Wang, Wang, and Shen (2016)	FS	√		st, det		√	C_{max}			HCS			DPFSP
Li et al. (2016)	FS		√	st, det		√	C_{max}		√	SA			DPFSP
Ji et al. (2016)	FS	√		st, stoch		√	C_{max}			PSO + SA			DAPFSP
Lin and Zhang (2016)	FS	√		st, det		√	C_{max}			BBO			DAPFSP
Companys and Ribas (2016)	FS	√		st, det		√	C_{max}			Heuristics			DBFSP
Wang and Wang (2016)	FS	√		st, det		√	C_{max}			EDA + MA			DAPFSP
Rifai, Nguyen, and Dawal (2016)	FS	√		st, det		√	C_{max}, T_{avg}, Cost		√	ALNS			DPFSP
Ying et al. (2017)	FS	√		st, det		√	C_{max}			IGA			DNIPFSP
Ribas, Companys, and Tort-Martorell (2017)	FS	√		st, det		√	C_{max}		√	ILS, IGA			DBFSP
Shao, Pi, and Shao (2017a)	FS	√		st, det		√	C_{max}			Hybrid IGA			DNFSP
Komaki and Malakooti (2017)	FS	√		st, det		√	C_{max}			GVNS			DNFSP
Shao, Pi, and Shao (2017b)	FS	√		st, det		√	C_{max}			Hybrid IGAs			DNFSP
Bargaoui, Driss, and Ghédira (2017a)	FS	√		st, det		√	C_{max}			CRO			DPFSP
Gonzalez-Neira et al. (2017)	FS	√		st, det		√	C_{max}			Heuristic	√		DAPFSP

Author and year	Shop configuration	Factory type		Demand	Network structure		Objective	Solution method					Specific problem
		hom	het		serial	par		Exact	IP	Heuristic/Meta-heuristic	Sim.	Other	
Bargaoui, Driss, and Ghédira (2017b)	FS	√		st, det		√	C_{max}			CRO	√		DPFSP
Dempster, Li, and Drake (2017)	FS	√		st, det		√	C_{max}			DEA			DTMFSP
Lin, Wang, and Li (2017)	FS	√		st, det		√	C_{max}			BSH			DAPFSP
Ying and Lin (2017)	FS	√		st, det		√	C_{max}		√	HIGA			DBFSP
Zhang, Xing, and Cao (2018a)	FS	√		st, det		√	C_{max}			DEA			DBFSP
Wang and Wang (2018)	FS	√		st, det		√	C_{max}, TEC			KCA			DPFSP
Zhang and Xing (2018)	FS	√		st, det		√	$\sum Cj$			MSSO			DTSAFSP
Zhang, Xing, and Cao (2018b)	FS	√		st, det		√	C_{max}		√	Heuristic, hybrid VNS, hybrid PSO			DFSP-FAST
Hatami et al. (2018)	FS	√		st, det		√	C_{max} (st/det), C_{max} percentile			ILS	√		DFSP
Fernandez-Viagas, Perez-Gonzalez, and Framinan (2018)	FS	√		st, det		√	$\sum Cj$		√	Heuristic, EA			DPFSP
Ying and Lin (2018)	FS	√		st, det		√	C_{max}		√	IGA			DFSP
Pan, Gao, Wang, et al. (2019)	FS	√		st, det		√	$\sum Cj$			Heuristics, ABC, IGA, SS, ILS			DPFSP
Ruiz, Pan, and Naderi (2019)	FS	√		st, det		√	C_{max}			IGA			DPFSP
Hao et al. (2019)	FS	√		st, det		√	C_{max}			BSO			DFHSP
Pan, Gao, Xin-Yu, et al. (2019)	FS	√		st, det		√	C_{max}		√	Heuristics, VNS, IGA			DAPFSP
Bok, Grossmann, and Park (2000)	JS		√	dyn, det		√	Profit	√	√				
Thoney et al. (2002)	JS	√		st, det	√		T_{max}			Heuristic			
Moon, Kim, and Hur (2002)	JS		√	dyn, det		√	$\sum T_j$		√	GA			
Jia et al. (2003)	JS	√		st, det	√		C_{max} + Cost			GA			
Karageorgos et al. (2003)	JS		√	dyn, det		√	$\sum C_j$ + Cost				√		
de Matta and Miller (2004)	JS		√	dyn, det	√		Cost	√	√				
Chan, Chung, and Chan (2005)	JS	√		st, det		√	C_{max}			GA			DFJSP
Moon and Seo (2005a)	JS	√		st, det		√	C_{max}		√	GA			
Moon and Seo (2005b)	JS		√	st, det		√	C_{max} + M_{util}		√	GA			
Chan, Chung, and Chan (2006)	JS		√	st, det		√	C_{max}		√	GA			DFJSP
Moon et al. (2006)	JS		√	st, det		√	C_{max}		√	Hybrid GA			
Chan et al. (2006)	JS		√	st, det		√	C_{max}		√	GA			DFJSP
Lau et al. (2006)	JS		√	st, det		√	Cost		√		√		
Jia et al. (2007)	JS	√		st, det		√	C_{max}, $\sum T_j$, Cost			GA			
Chan and Chung (2007)	JS		√	st, det		√	C_{max}		√	GA			
Chan, Kumar, and Mishra (2008)	JS		√	dyn, det		√	$\sum T_j$		√	PSO			
Chung, Chan, and Chan (2009)	JS		√	st, det		√	C_{max}		√	GA			
Chung et al. (2009)	JS		√	st, det		√	C_{max}		√	GA			
Kopanos and Puigjaner (2009)	JS		√	dyn, det		√	Cost		√				
Chung et al. (2010)	JS		√	dyn, det	√	√	C_{max}		√	GA			

Author and year	Shop configura-tion	Factory type		Demand	Network structure		Objective	Solution method					Specific problem
		hom	het		serial	par		Exact	IP	Heuristic/Meta-heuristic	Sim.	Other	
De Giovanni and Pezzella (2010)	JS		√	st, det		√	C_{max}			GA			DFJSP
Lou, Ong, and Nee (2010)	JS		√	dyn, det		√	C_{max}				√		
Lawrynowicz (2011)	JS		√	st, det		√	C_{max}			GA			
Aissani et al. (2012)	JS		√	dyn, det		√	C_{max}		√		√		DFJSP
Chan et al. (2013)	JS		√	st, det		√	C_{max}		√	TS + SA			DFJSP
Guo et al. (2013)	JS		√	st, det		√	M_{util}, $\sum T_j, \sum C_j$		√	GA	√		
H'Mida and Lopez (2013)	JS		√	st, det	√	√	$\sum C_j$					CP	
Lim, Tan, and Leung (2013)	JS		√	st, det		√	Cost			GA	√		
Ziaee (2014)	JS		√	st, det		√	C_{max}			Heuristic			DFJSP
Archimede et al. (2014)	JS		√	st, det		√	$\sum T_j$				√		
Naderi and Azab (2014)	JS	√		st, det		√	C_{max}		√	Heuristics			
Liu, Chen, and Chou (2015)	JS		√	st, det		√	C_{max}			GA			
Naderi and Azab (2015)	JS	√		st, det		√	C_{max}		√	SA			
Sun, Chung, and Chan (2015)	JS		√	st, det	√	√	Cost		√	Heuristic, GA			
Lu et al. (2015)	JS		√	st, det		√	C_{max}			GA			DFJSP
Guo et al. (2015)	JS		√	dyn, stoch		√	$\sum T_j + \sum C_j + M_{util}$		√	HS	√		
Chang and Liu (2017)	JS		√	st, det		√	C_{max}			Hybrid GA			DFJSP
Wu et al. (2017)	JS		√	st, det		√	C_{max}			GA			DFJSP
Chaouch, Driss, and Ghedira (2017a)	JS	√		st, det		√	C_{max}			ACO			
Chaouch, Driss, and Ghedira (2017b)	JS	√		st, det		√	C_{max}			ACO			
Marzouki, Driss, and Ghedira (2018)	JS		√	st, det		√	C_{max}			TS	√		
Wang, Yang, and Yu (2018)	JS	√		dyn, stoch		√	Service + $\sum C_j$ + Cost + Profit + M_{util}					√	
Jia et al. (2002)	OS	√		st, det		√	C_{max}, Cost			GA	√		
Li and Ou (2007)	OS		√	st, det		√	Cost			Heuristics			

SM = Single machine, PM = Parallel machine, FS = Flowshop, JS = Jobshop, OS = Open shop, hom = homogenous, het = heterogeneous, par = parallel, IP = Integer programming, Sim. = Simulation, MAS = Multi-agent system, NLP = Non-linear programming, CP = Constraint programming, Dyn. Pr. = Dynamic programming, TIM = Time-indexed model

ABC = Artificial bee colony algorithm, ACO = Ant colony optimisation, ALNS = Adaptive large neighbourhood search, B&B = Branch & Bound, BBO = Biography-based optimisation, BSH = Backtracking search hyper-heuristic, BSIG = Bounded-search iterated greedy alg., BSO = Brain storm optimisation algorithm, CDS = Campbell-Dudek-Smith heuristic, CMA = Competitive memetic algorithm, CRO = Chemical reaction optimisation, CP = Constraint programming, DDE = Discrete differential evolution alg., DEA = Differential evolution algorithm, DES = Discrete event simulation, EA = Evolutionary algorithm, EAS = Elitist ant system, EDA = Estimation of distribution algorithm, EDAMA = Estimation of distribution-based memetic algorithm, EM = Electromagnetism mechanism, GA = Genetic algorithm, GRASP = Greedy randomised adaptive search procedure, GVNS = General variable neighbourhood search, HCS = Hybrid cuckoo search, HIA = Hybrid immune algorithm, HIGA = Hybrid iterated greedy algorithm, HS = Harmony search, IA = Immune algorithm, ICA = Imperialist competitive algorithm, ICG = Iterated cocktail greedy algorithm, IGA = Iterated greedy algorithm, ILS = Iterated local search, KCA = Knowledge-based cooperative algorithm, LPT = Largest processing time, LRPT = Largest remaining processing time, LS = Local search, MA = Memetic algorithm, MAS = Multi-agent system, MCS = Monte Carlo simulation, MILP = Mixed-integer linear programming, MSSO = Memetic social spider optimisation algorithm, NLP = Non-linear integer programming, NEH = Nawaz-Enscore-Ham heuristic, NEH2 = NEH, assigning job j to the factory with the lowest Cmax after including job j, PSO = Particle swarm optimisation, RVNS = Reduced variable neighbourhood search, SA = Simulated annealing, SPT = Shortest processing time, SS = Scatter search, TS = Tabu search, VNS = Variable neighbourhood search, VND = Variable neighbourhood descent

4. Objectives and solution methods

In this section, we analyse the objective functions and solution methods used in literature in more detail (RQ2). Similar to the literature on traditional production scheduling, minimising the makespan is the most common objective used for distributed problems (Rossit, Tohmé, and Frutos 2018; Allahverdi 2015). Solution methods are very diverse and differ depending on the shop configuration and an overall trend to use meta-heuristics is apparent in all areas.

4.1 Objectives

To determine the (near) optimal sequence of jobs in the multi-factory setting, an appropriate performance measure has to be defined. Following the three-field notation $\alpha/\beta/\gamma$ of Graham et al. (1979), the third field (γ) represents the performance measure or objective. We analysed the literature accordingly. Table 3 indicates the identified objectives and their abbreviations (as used in Table 2) (Pinedo 2014).

Table 3. Problem characteristics / objective function

C_{max}	Makespan	M_{util}	Machine utilisation (or workload)
$\sum C_j$	Total Completion time	M_{setup}	Setup times
$\sum T_j$	Total Tardiness	Service	Service level (or throughput)
$\sum E_j$	Total Earliness	Inv.	Inventory
T_{max}	Maximum Tardiness	TEC	Total energy consumption
T_{avg}	Average Tardiness	Cost	Cost
$\sum T_j + \sum E_j$	Due Date (Tardiness & Earliness)	Profit	Profit

In the case of time-related measures, we distinguish between total and maximum values, but not between the minimisation of total or mean of time-related measures as this results in the same solution (Allahverdi 2015). For instance, total tardiness $\sum T_j$ and mean tardiness $\sum T_j/n$ are referred to simply as $\sum T_j$. If more than one objective is examined, we distinguish between a separate consideration and a multi-criteria problem. One example for the first type is C_{max}, TEC (Wang and Wang 2018), where the authors address both the problems C*max* and TEC separately. Multi-criteria problems are indicated by a combination, e.g. $\sum T_j + \sum C_j + M_{util}$ (Guo et al. 2015), indicating a Pareto approach or a linear combination. The pursued optimisation criteria of the single objective articles on distributed scheduling are summarised in Fig. 8.

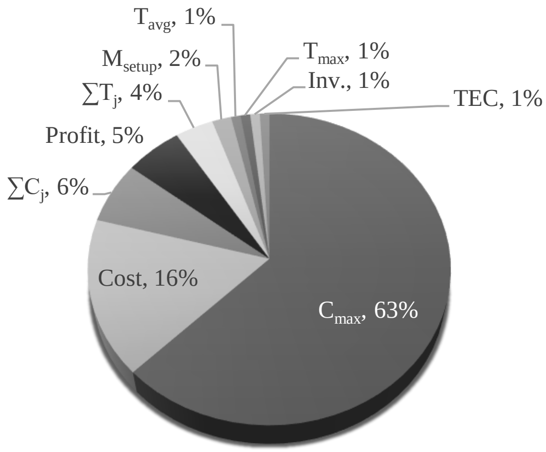

Figure 8. Optimisation criteria of single objective articles on multi-factory production planning and scheduling

Similar to the general scheduling literature, the most frequently used objective is the minimisation of makespan C_{max} (63%, 69 publications). This is reasonable, as reducing the makespan is strongly related to resource utilisation (Allahverdi 2015). The majority of articles focusing on C_{max} deal with flowshop (39 articles) and jobshop (24 articles). 18 publications aim for cost minimisation (6 in *SM*, 5 in *JS*) and, in 7 cases (4 in *FS*), total completion time is minimised. The ratio of earliness/tardiness oriented contributions is rather low compared to single factory scheduling (Allahverdi 2015), although on-time delivery is vital in several industries facing fierce competition. If the time relation is considered when analysing the most important objectives (C_{max}, Cost, $\sum C_j$, and Profit), a significant increase in articles focusing on C_{max} can be observed (2000 – 2009: 8 articles, 2010 – 2019: 61 articles), while the number of articles on profit and $\sum C_j$ remains rather constant (1 – 2 articles per year) and costs are considered quite irregularly.

Bi- or multi-criteria objective functions are considered in 25 articles (20%). The majority of bi- or multi-objective problems addressed costs (see Table 4). Cost and C_{max} were examined 5 times, followed by due date ($\sum T_j + \sum E_j$) and costs in 4 articles and $\sum C_j$ and costs in three contributions. It is apparent that several objectives and their combinations have not been addressed including setup times/costs, inventory levels/costs, and energy consumption/costs. Profit is also quite underrepresented and studied in only 8 contributions overall (4 in multi-objective considerations). Table 4 shows the frequencies of the identified combinations over all shop configurations.

Table 4. Bi- and multi-objective contributions, breakdown of objective appearance

	C_{max}	$\sum C_j$	$\sum T_j$	$\sum T_j + \sum E_j$	M_{util}	M_{setup}	Service	Inventory	TEC	Cost	Profit
C_{max}	-	2	1		1		2		1	5	1
$\sum C_j$	2	-	1		1					3	
$\sum T_j$	1	1	-		3		1			2	
$\sum T_j + \sum E_j$				-	2			1		4	
M_{util}	1	1	1	2	-		2	1		2	
M_{setup}						-		1			
Service	2				2		-	1		2	1
Inventory					1	1	1	-			
TEC	1			1					-		
Cost	5	3	2	4	2		2			-	2
Profit	1						1			2	-

4.2 Solution methods

The models in multi-factory production planning and scheduling are known to be NP-hard, requiring high computational effort. Different solution methods were observed in literature as displayed in Fig. 9. Certainly, some authors apply several solution methods concurrently. In total, 59 articles present programming models, either mixed-integer (MIP) or mixed-integer linear (MILP) models. Only 9 articles use exact algorithms, like Branch & Bound (B&B) to solve multi-factory problems optimally. Most publications focus on heuristic and meta-heuristic approaches due to the computational complexity of the problems and the potential for rapid convergence towards good solutions. While 19 articles design or utilise simpler heuristics, 93 articles propose or utilise meta-heuristic algorithms. Simulation was used in 10 articles. Besides, 15 methods were classified as ‘other’ due to their rare use. In 11 of these articles, MAS were used to schedule or coordinate the different factories. We analyse the different solution methods in the following subsections, starting with exact approaches. The programming models are not analysed in detail due to the diversity of the problem formulations. We refer to Appendix 1 for this as well as for the analysis of the simulation methods and the ‘other’ solution methods.

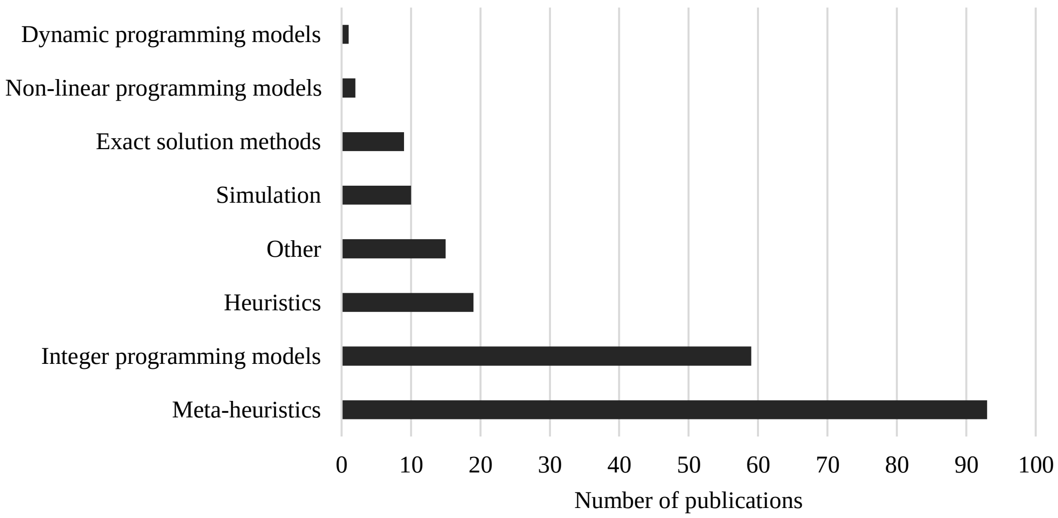

Figure 9. Number of publications by solution methods

4.2.1 Exact approaches

The mathematical formulations of multi-factory problems can theoretically be solved to optimality. However, due to the NP-hard nature of the problems, exact solution methods and MIP models are computationally expensive and capable of solving small to medium size problems only, typically up to 12 jobs, 5 machines, and 3 factories (Ying and Lin 2018; Naderi and Ruiz 2010). Most of the authors simplify the optimisation models by removing constraints to then optimally solve the relaxed problem. The optimum of the relaxed problem is equal to the optimum of the original problem if it satisfies the relaxed constraints. In general, relaxations provide only a lower bound on the optimum of the original problem but are significantly less expensive to compute.

Exact solution approaches in the multi-factory environment include bi-level decomposition (Bok, Grossmann, and Park 2000; Terrazas-Moreno and Grossmann 2011), augmented Lagrangean decomposition (Shah and Ierapetritou 2012), and multi-cut Benders decomposition (Behnamian 2015). Other authors use B&B (Bok, Grossmann, and Park 2000; De Matta and Miller 2004; Karimi and Davoudpour 2015) or mathematical programming (Garcia, Lozano, and Canca 2004; Ruifeng and Subramaniam 2011; Cóccola et al. 2013).

In recent years, the combination of exact methods with heuristics to provide upper or lower bounds seems promising, e.g. for the B&B search (Karimi and Davoudpour 2015). Notably, most exact solution approaches are applied in *SM* or *PM* settings only (three articles each). This is due to the relatively moderate complexity of *SM* and *PM* problems. Overall, however, the computational complexity in real-world instances led to extensive research of heuristics and meta-heuristics, taking into account the uncertainty of determining an optimal solution.

4.2.2 Heuristics

Heuristics are problem-oriented and determine solutions according to a set of rules. They are designed to be implemented easily and try to exploit the specific problem structure effectively to achieve near-optimal solutions in a short timeframe. While constructive heuristics create an initial solution with the best possible results, improving heuristics are aimed at improving an existing initial solution (Pinedo 2014). Heuristics are increasingly researched in multi-factory configurations (see Table 2). Again, FS accounts for the largest share of contributions using heuristics (9 of 19 articles). For the DPFSP, Naderi and Ruiz (2010) tested six heuristics from the PFSP literature and concluded that NEH by Nawaz, Enscore, and Ham (1983), using the Taillard (1990) accelerations, performed best. To use the NEH for the sequencing decision, two simple assignment rules are proposed. In NR1, job *j* is assigned to the factory with the lowest current C_{max} not including job *j*. In NR2, job *j* is assigned to the factory with the lowest C_{max} after including job *j*. In this way, all *m* tasks of job *j* are sequenced at all factories, which is more complex to compute, but proved to be more effective than NR1. Other authors also successfully applied the NEH heuristic in different approaches: Companys and Ribas (2016) for the DBFSP, Fernandez-Viagas, Perez-Gonzalez, and Framinan (2018) to minimise total flowtime in the DPFSP and Pan, Gao, Xin-Yu, et al. (2019) for the DAPFSP with a single assembly machine in each factory.

In general, many authors have achieved good results with adapted heuristics from the area of traditional scheduling. Depending on the specific problem, the heuristics designed for this specific problem in traditional scheduling of a single factory often performed well in the distributed, multi-factory case too. Companys and Ribas (2016) confirm this hypothesis in their study for the DBFSP where they compared 33 constructive heuristics. Other adapted heuristics include a modified minimum slack heuristic for batch processing (Thoney et al. 2002), a modified LPT heuristic for *PM* (Behnamian and Fatemi Ghomi 2013), SPT-based and other constructive heuristics for the DAPFSP by Hatami, Ruiz, and Andrés-Romano (2013) and again including sequence-dependent setup times (Hatami, Ruiz, and Andrés-Romano 2015). Lately, several authors utilised constructive heuristics for DPFSP and DAPFSP configurations (Zhang, Xing, and Cao 2018b; Fernandez-Viagas, Perez-Gonzalez, and Framinan 2018; Pan, Gao, Xin-Yu, et al. 2019; Pan, Gao, Wang, et al. 2019).

In summary, scholars should extend more of the classical, performant heuristics from traditional scheduling to the distributed configuration as their performance is promising. Heuristics are also particularly valuable for good start solutions for certain meta-heuristics, which are discussed in the next subsection.

4.2.3 Meta-heuristics

In contrast to problem-dependent and specific heuristics, meta-heuristics represent more general algorithms that iteratively achieve an optimised solution based on the efficient exploration of a specified search space (Talbi 2009). Meta-heuristics have been successfully applied to a variety of NP-hard optimisation problems (Pan, Gao, Wang, et al. 2019). Single solution based meta-heuristics like local search (LS), tabu search (TS) or simulated annealing (SA) improve a single solution, ‘moving’ through the search space. Population-based meta-heuristics like genetic algorithms (GA), particle swarm optimisation (PSO) or estimation of distribution algorithms (EDA) try to find an iterative improvement in a population of solutions. More than half of all articles using meta-heuristics have been published in the last five years (50 out of 93 articles). The most important meta-heuristics are indicated and analysed in the following sections.

4.2.3.1 Genetic algorithms. Genetic algorithms are most frequently used to solve multi-factory problems. 29 contributions use a GA or a hybrid variant to obtain a near-optimal solution. GAs are based on the genetic process of biological organisms that evolve according to natural selection (De Giovanni and Pezzella 2010). Interestingly, 19 articles use GA for JS, which is related to the complexity of distributed job shops and the opportunity to use a single chromosome representation to enable the GA to converge to a good solution swiftly. 7 articles focus on multi-objective problems, while in other contributions GA is successfully hybridised with different approaches: fuzzy logic (Chang and Liu 2017), local search (e.g. Moon et al. 2006), variable neighbourhood search (VNS) (Xiong et al. 2014; Xiong and Xing 2014), simulated annealing (Kerkhove and Vanhoucke 2014) and fuzzy-logic based EDA (Wang, Huang, and Qin 2016).

4.2.3.2 Iterated greedy algorithms. 9 articles, all published in the last five years exclusively for FS problems, focus on iterated greedy algorithms. IGAs typically consist of initialisation, construction and destruction procedures with an acceptance criterion and are simple to set up and apply (Jacobs and Brusco 1995). Typically, at least one local search method is included in the algorithmic procedure. The DPFSP can be solved by IG methods very effectively (Lin, Ying, and Huang 2013; Fernandez-Viagas and Framinan 2015). A comparison of the recent and promising algorithms by Pan, Gao, Wang, et al. (2019) and Ruiz, Pan, and Naderi (2019) is currently outstanding. IGAs were also presented for the DBFSP (Ribas, Companys, and Tort-Martorell 2017), DNFSP (Shao, Pi, and Shao 2017a, 2017b), DAPFSP (Pan, Gao, Xin-Yu, et al. 2019), the no-idle FS (Ying et al. 2017) and the DPFSP with multi-processor tasks (Ying and Lin 2018).

4.2.3.3 Variable neighbourhood search. Another set of 8 articles applies variable neighbourhood search techniques. Based on a single initial solution, the neighbourhood structure is altered in a VNS in the search process to avoid falling into local optima. General VNS was proposed for a glass container industry case study (Almada-Lobo, Oliveira, and Carravilla 2008), the DNFSP (Komaki and Malakooti 2017), and the DAPFSP (Pan, Gao, Xin-Yu, et al. 2019). Other authors combined VNS with TS (Behnamian 2014), GA and differential evolution (Xiong et al. 2014), electro-magnetism matheuristic (Behnamian 2017b) and PSO (Zhang, Xing, and Cao 2018b).

4.2.3.4 Simulated annealing. The traditional simulated annealing meta-heuristic is based on the annealing procedure in metallurgy. Only a single solution is carried over to the next iteration (Pinedo 2014). 6 articles use SA to find solutions for *PM*, *FS* or *JS*. General SA methods were proposed by Azevedo and Sousa (2000) and Naderi and Azab (2015). Other authors use meta-heuristic combinations (Chan et al. 2013; Kerkhove and Vanhoucke 2014; Ji et al. 2016). The basic idea of SA has also been incorporated in other efficient heuristics, e.g. LS (Li et al. 2016).

4.2.3.5 Tabu and scatter search. Similar to simulated annealing, tabu search and scatter search techniques are not employed frequently for multi-factory problems (6 articles). Gao, Chen, and Deng (2013) use a TS recording the exchange of job sub-sequences for the DPFSP with C_{max} objective. Other contributions use hybrid approaches: TS & SA (Chan et al. 2013), TS & VNS (Behnamian 2014) and TS & MAS (Marzouki, Driss, and Ghedira 2018). The SS approach by Naderi and Ruiz (2014) was recently outperformed by an improved SS method (Pan, Gao, Wang, et al. 2019).

4.2.3.6 Particle swarm optimisation. Particle swarm optimisation algorithms mimic the behaviour of organisms that live and evolve in swarms, moving towards efficient solutions collaboratively in the search space. In the context of distributed manufacturing, algorithms were presented by Chan, Kumar, and Mishra (2008) and Behnamian (2016, 2017b) as well as Ji et al. (2016) and Zhang, Xing, and Cao (2018a) for hybridised variants.

4.2.3.7 Other sophisticated meta-heuristics. Apart from these methods, an increasing number of articles applied non-traditional optimisation approaches to the different distributed problem variants. Imperialistic competition algorithms (ICA) are popular for single and parallel machine configurations. ICAs originate from evolution processes in colonisation (Behnamian and Fatemi Ghomi 2012; Karimi and Davoudpour 2017b; Lei et al. 2019; Marandi and Fatemi Ghomi 2019). On the other hand, memetic algorithms that combine evolutionary search and problem-specific local search techniques have solely been developed for FS (Deng, Wang, Wang, et al. 2016; Wang and Wang 2016; Zhang and Xing 2018).

Nature-inspired algorithms proposed for multi-factory settings include artificial bee colony algorithms (Yazdani, Gohari, and Naderi 2015; Pan, Gao, Wang, et al. 2019), cuckoo search (Wang, Wang, and Shen 2016) and ant colony optimisation (Chaouch, Driss, and Ghedira 2017a; 2017b). Other authors applied chemical reaction optimisation (Bargaoui, Driss, and Ghédira 2017a; 2017b), estimation of distribution algorithms (Wang et al. 2013; Wang, Huang, and Qin 2016; Wang and Wang 2016) and harmony search methods (Guo et al. 2015; Deng, Wang, Shen, et al. 2016).

4.2.4 Other solution methods and combinations

Some authors apply simulation and other solution methods to multi-factory problems that are often combined with (meta-)heuristics. These methods are useful in uncertain manufacturing environments or for multi-objective decisions. Among the combinations are a hybrid MAS and DES for *SM* (Nigro et al. 2003), a wasp-like MAS approach for *PM* (Cicirello and Smith 2004), a distributed MAS for multi-tier and multi-site production (Chen, Huang, and Lai 2009), and agent-based models (Karageorgos et al. 2003; Lau et al. 2006). Virtual shops with distributed resources (*JS*) were studied using MAS by Lou, Ong, and Nee (2010) and Archimede et al. (2014), whereby Behnamian and Fatemi Ghomi (2012) focused on *PM*. Aissani et al. (2012) used reinforcement learning in an MAS for flexible *JS* to reach real-time decisions. Lim, Tan, and Leung (2013) applied a currency-bidding mechanism combined with a GA. The combination of MAS with meta-heuristics has become more popular recently with contributions by Bargaoui, Driss, and Ghédira (2017b) using a chemical reaction optimisation (CRO) meta-heuristic with an

MAS for the DPFSP and Marzouki, Driss, and Ghedira (2018) combining a tabu search (TS) with an MAS for the DFJSP.

Other combinations presented include hybrid MILP and simulation models (Gnoni et al. 2003), a Pareto optimisation model with a GA and a production process simulation (Guo et al. 2013), constraint-based scheduling using simulation in a two-phase approach (Chen 2014) and Monte Carlo simulation (MCS) in simheuristics (Guo et al. 2015; Gonzalez-Neira et al. 2017; Hatami et al. 2018).

5. Directions for further research and managerial implications

5.1 Directions for further research

Due to the advancing digital transformation, Industry 4.0 and tendencies to form collaborative networks to minimise costs and time-to-market (Hosseini and Tan 2019; Parente et al. 2020), there is a growing interest in multi-factory production planning and scheduling. Therefore, our results may indicate some fruitful directions for further studies (RQ3).

In the context of decentralised scheduling and autonomous decision-making, flexibility is a major requirement to utilise multi-agent and multi-factory systems accordingly (Parente et al. 2020). Particularly in a multi-factory environment, scholars should focus more on flexible problems and consider options like using more than one resource simultaneously (multi-processor scheduling) or different modes (multi-mode scheduling). Transportation-related costs (accounting for the largest share in geographically distributed production) need to be considered in any case, so that the effect on the profitability of transferring orders in progress to other factories can be examined (Marandi and Fatemi Ghomi 2019).

Implications for further studies considering objective functions include objectives such as earliness/tardiness to meet quoted due dates which are vital to ensure on-time delivery to meet customer demands and fulfil just-in-time principles in supply chains (Karimi and Davoudpour 2015; Guo et al. 2015). In addition, the use of stochastic parameters (e.g. uncertain demand, due dates, processing times or random machine breakdowns) represents an area with potential. With constant real-time data available throughout the enterprise and new analysis tools, production can be better aligned with upstream and downstream logistics processes. Integrated production and distribution scheduling is also a vital area for further studies, especially when more than one delivery mode is available (Harjunkoski et al. 2014; Chen 2010; Fu, Aloulou, and Triki 2017).

Frequently, problem sizes in multi-factory problems surpass levels that exact solution methods can cope with. Meta-heuristic techniques have proven to be a vital alternative to constructive heuristics in real-world cases as they offer significant improvement potential in reasonable computation time and often remain the only option for large problems (Kerkhove and Vanhoucke 2014). Further meta-heuristics should be extended to multi-factory problems, as new methods (e.g. hybridisations) are regularly introduced for traditional single-factory scheduling (Allahverdi 2015). On top of this, holistic scheduling using information from various sources available in real-time has to be extended to multi-factory problems using techniques like machine learning or hyper-heuristics (Rossit, Tohmé, and Frutos 2019; Parente et al. 2020). Cloud computing might provide a way to address the complexity of emergent challenging problems.

Resilience plays a vital role in increasingly complex supply chains and production networks. A strategy frequently recommended and applied in practice is creating redundancy to counter disruptions more resiliently (Tukamuhabwa et al. 2015; Ivanov, Dolgui, and Sokolov 2019). Redundancy of capacities can be maintained in different factories to complete production orders in case of a disruption affecting a factory in the network. The use of these multi-factory environments to increase resilience and their influence on further SC resilience strategies is another interesting field of research. In a similar way, the future of production is seen in the cloud manufacturing paradigm, where distributed resources are pooled into reconfigurable and flexible manufacturing lines (Y. Liu et al. 2018). The way in which this paradigm can be integrated into existing and new networks still needs to be investigated in detail.

In addition, ecological and environmental aspects are becoming increasingly important for customers regarding the production of their consumed goods. The manufacturing location as a key purchase argument can have both positive and negative effects on sales. These aspects should find their way into the consideration of algorithms and models, as they may restrict the leeway of production networks. On the other hand, there is a tendency to align the capacities and production possibilities of individual factories (Argoneto and Renna 2016), which shifts the focus towards a strategic rather than an operative approach to factory allocation for the future.

Through methods such as additive manufacturing, there will be a more significant time- and process-related convergence of product development and manufacturing. This will encourage a trend towards foundry manufacturing in the future, which should be a topic for future research. Furthermore, decentralisation is often invoked by academics as a corollary in the context of new Industry 4.0 technologies (Rossit, Tohmé, and Frutos 2019; Babich and Hilary 2020; Y. Liu et al. 2018). Distributed ledger (blockchain) or industrial IoT technologies will enable methods like dynamic (online) scheduling and re-scheduling to become more relevant in the future due to more information that is available in real-time, which requires further research efforts. From an organisational perspective, local optimisation in decentralised factories must be evaluated critically as it tends to be directed towards local optima rather than a global optimum in a manufacturing network if autonomous agents independently deal with manufacturing locally (Parente et al. 2020).

Empirical studies are necessary to gain knowledge about the state-of-the-art of planning and scheduling of companies and production networks that rely on multiple factories. This is a research area that is currently clearly underrepresented in the scientific community (Olhager and Feldmann 2018) and is gaining in importance due to the Industry 4.0 trends and the global need for flexibility and agility. Valuable research directions include examining the distribution of decision-making structures in distributed manufacturing, revealing if and how the potential of multi-factory networks have been used and the state of collaboration among factories in these distributed networks.

5.2 Practical relevance and managerial implications

The practical relevance of multi-factory approaches is emphasised by the various application examples in the introduction and Appendix 1 of this study. The interested reader is provided with the current state-of-the-art in a comprehensive way. Besides, several research directions that can be addressed by science and industry were identified. Multi-factory companies need to exploit the potential arising from regional disparities in terms of resilient performance and cost savings to stay competitive. From a single factory approach, assigning orders to a factory based on a pre-defined allocation, managers need to be aware of opportunities when switching to a multi-factory planning model to ensure order fulfilment. POM practitioners could therefore use insights from this review to employ a model and/or algorithm presented in this review that fits their specific needs regarding shop configuration, production volumes and characteristics. It is especially important to develop a model that covers as many of the restrictions and influencing variables of the individual case as possible. Otherwise, decisions on incomplete information may lead to suboptimal capacity utilisation or financial performance in the short or long term.

Many industries examined by academics mainly profit from geographically separated factories and different wage levels. However, even industries with multiple factories in the same region can benefit from accelerated deliveries and ensure on-time delivery when the ability to plan, control and schedule multiple factories is identified and utilised. In the long run, strategic decisions on how to equip factories are equally important. Redundancy of manufacturing capabilities and capacities to enhance supply chain risk management can only be achieved through targeted investments that represent strategic decision scenarios.

6. Conclusion and limitations

A growing number of manufacturing firms are establishing intra-firm networks consisting of several geographically dispersed factories. This article provides a comprehensive and systematic review of the available literature on multi-factory production planning and scheduling problems. We analysed and classified 128 contributions from literature according to shop configuration, factory type, demand, network structure, objective functions and solution methods (RQ1). In-depth consideration of objective functions and solution methods (RQ2) indicated that adapted heuristics from traditional scheduling performed well in the distributed case too. Genetic algorithms and iterated greedy algorithms are meta-heuristics which, due to their flexibility and efficiency, are most frequently applied to handle large instances of these NP-hard problems.

Minimising makespan dominates the literature, while several objectives, e.g. due date related (earliness & tardiness) have hardly been considered. This is also true for stochastic influences such as maintenance measures or uncertain demand. The bibliometric analysis revealed that academic attention has increased over the last decade, focusing on flowshops and jobshops. A trend from genetic algorithms to iterated greedy algorithms, knowledge-based systems and learning algorithms for the different multi-factory problems is apparent. Directions for further research (RQ3) include studying integrated problems, utilising adopted sophisticated meta-heuristics, examining neglected performance measures and the interconnection of multi-factory configurations with related research disciplines: supply chain resilience, ecological studies, new Industry 4.0 trends like decentralisation and IoT and efficient network configuration in management research. Scientific efforts are vital for the industry moving towards multi-factory networks and collaborative inter- and interorganisational production due to globalisation and digital transformation.

The presented contribution certainly has limitations. The final literature set was generated by searching four scholarly databases using the mentioned keywords, with specific inclusion and exclusion criteria (Cooper 1988). Although we tried to be as comprehensive as possible, we might not have incorporated all keywords necessary to obtain all relevant publications. The selection process of the literature set may be biased, even though we have taken every effort to minimise this potential bias. For instance, we included conference proceedings in the analysis, which could lead to a certain bias compared to other studies. However, in our view, the benefit of being comprehensive and exhaustive outweighed this potential bias since the topic is so rapidly evolving and innovative. We also explicitly included only peer-reviewed articles, limiting the bias to a certain extent. Due to the size of our literature set, the recommendations for further research provided are probably not comprehensive for all sub-areas and problems of multi-factory production planning and scheduling. Instead, we focused on the most important issues and hope that the detailed analysis in the Appendix will satisfy any need for additional information and interpretation. Another limitation of this study is the exclusion of empirical studies from this review that might have revealed other specific managerial implications. We recommend further empirical studies in this domain.

Appendix

The appendices are available at http://dx.doi.org/10.25532/OPARA-57 (Appendix 1) and http://dx.doi.org/10.25532/OPARA-58 (Appendix 2).

Acknowledgement

The authors would like to express their sincere thanks to the two anonymous reviewers and the associate editor who have contributed to the improvement of earlier versions of this paper.

This research was supported in part by the EU project iDev40. The iDev40 project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 783163. The JU receives support from the European Union's Horizon 2020 research and innovation program. It is co-funded by the consortium members, as well as grants from Austria, Germany, Belgium, Italy, Spain, and Romania. The content of this article does not reflect the official opinion of the Joint Undertaking ECSEL. Responsibility for the information and views expressed in the article lies entirely with the authors.

References

Aissani, N., A. Bekrar, D. Trentesaux, and B. Beldjilali. 2012. "Dynamic Scheduling for Multi-Site Companies: A Decisional Approach Based on Reinforcement Multi-Agent Learning." *Journal of Intelligent Manufacturing* 23 (6): 2513–2529. doi:10.1007/s10845-011-0580-y.

Allahverdi, Ali. 2015. "The Third Comprehensive Survey on Scheduling Problems with Setup Times/Costs." *European Journal of Operational Research* 246 (2): 345–378. doi:10.1016/j.ejor.2015.04.004.

Allahverdi, Ali, C. T. Ng, T. C.E. Cheng, and Mikhail Y. Kovalyov. 2008. "A Survey of Scheduling Problems with Setup Times or Costs." *European Journal of Operational Research* 187 (3): 985–1032. doi:10.1016/j.ejor.2006.06.060.

Almada-Lobo, Bernardo, José F. Oliveira, and Maria Antónia Carravilla. 2008. "Production Planning and Scheduling in the Glass Container Industry: A VNS Approach." *International Journal of Production Economics* 114 (1): 363–375. doi:10.1016/j.ijpe.2007.02.052.

Alvarez, Esther. 2007. "Multi-Plant Production Scheduling in SMEs." *Robotics and Computer-Integrated Manufacturing* 23 (6): 608–613. doi:10.1016/j.rcim.2007.02.006.

An, Yu-Wei, and Hong-Sen Yan. 2016. "Lagrangean Relaxation Approach to Joint Optimization for Production Planning and Scheduling of Synchronous Assembly Lines." *International Journal of Production Research* 54 (22): 6718–6735. doi:10.1080/00207543.2016.1157271.

Archimede, Bernard, Agnes Letouzey, Muhammad Ali Memon, and Jiucheng Xu. 2014. “Towards a Distributed Multi-Agent Framework for Shared Resources Scheduling.” In *Journal of Intelligent Manufacturing,* 25:1077–1087. doi:10.1007/s10845-013-0748-8.

Argoneto, Pierluigi, and Paolo Renna. 2016. “Supporting Capacity Sharing in the Cloud Manufacturing Environment Based on Game Theory and Fuzzy Logic.” *Enterprise Information Systems* 10 (2): 193–210. doi:10.1080/17517575.2014.928950.

Azevedo, A. L., and J. P. Sousa. 2000. “Order Planning for Networked Make-to-Order Enterprises - a Case Study.” *Journal of the Operational Research Society* 51 (10): 1116–1127. doi:10.1057/palgrave.jors.2600066.

Babich, Volodymyr, and Gilles Hilary. 2020. “Distributed Ledgers and Operations: What Operations Management Researchers Should Know About Blockchain Technology.” *Manufacturing & Service Operations Management* 22 (2): 223–240. doi:10.1287/msom.2018.0752.

Bargaoui, Hafewa, Olfa Belkahla Driss, and Khaled Ghédira. 2017a. “A Novel Chemical Reaction Optimization for the Distributed Permutation Flowshop Scheduling Problem with Makespan Criterion.” *Computers and Industrial Engineering* 111: 239–250. doi:10.1016/j.cie.2017.07.020.

Bargaoui, Hafewa, Olfa Belkahla Driss, and Khaled Ghédira. 2017b. “Towards a Distributed Implementation of Chemical Reaction Optimization for the Multi-Factory Permutation Flowshop Scheduling Problem.” In *Procedia Computer Science,* 112:1531–1541. doi:10.1016/j.procs.2017.08.057.

Behnamian, J. 2014. “Decomposition Based Hybrid VNS-TS Algorithm for Distributed Parallel Factories Scheduling with Virtual Corporation.” *Computers and Operations Research* 52: 181–191. doi:10.1016/j.cor.2013.11.017.

Behnamian, J. 2015. “Multi-Cut Benders Decomposition Approach to Collaborative Scheduling.” *International Journal of Computer Integrated Manufacturing* 28 (11): 1167–1177. doi:10.1080/0951192X.2014.961963.

Behnamian, J. 2016. “Graph Colouring-Based Algorithm to Parallel Jobs Scheduling on Parallel Factories.” *International Journal of Computer Integrated Manufacturing* 29 (6): 622–635. doi:10.1080/0951192X.2015.1099074.

Behnamian, J. 2017a. “Heterogeneous Networked Cooperative Scheduling with Anarchic Particle Swarm Optimization.” *IEEE Transactions on Engineering Management* 64 (2): 166–178. doi:10.1109/TEM.2016.2642144.

Behnamian, J. 2017b. “Matheuristic for the Decentralized Factories Scheduling Problem.” *Applied Mathematical Modelling* 47: 668–684. doi:10.1016/j.apm.2017.02.033.

Behnamian, J., and S. M.T. Fatemi Ghomi. 2012. “Incorporating Transportation Time in Multi-Agent Production Network Scheduling.” *International Journal of Computer Integrated Manufacturing* 25 (12): 1111–1128. doi:10.1080/0951192X.2012.684716.

Behnamian, J., and S. M.T. Fatemi Ghomi. 2013. “The Heterogeneous Multi-Factory Production Network Scheduling with Adaptive Communication Policy and Parallel Machine.” *Information Sciences* 219: 181–196. doi:10.1016/j.ins.2012.07.020.

Behnamian, J., and S. M.T. Fatemi Ghomi. 2016. “A Survey of Multi-Factory Scheduling.” *Journal of Intelligent Manufacturing* 27 (1): 231–249. doi:10.1007/s10845-014-0890-y.

Bennett, Nathan, and G. James Lemoine. 2014. “What a Difference a Word Makes: Understanding Threats to Performance in a VUCA World.” *Business Horizons* 57 (3): 311–317. doi:10.1016/j.bushor.2014.01.001.

Bhatnagar, Rohit, Pankaj Chandra, and Suresh K. Goyal. 1993. “Models for Multi-Plant Coordination.” *European Journal of Operational Research* 67 (2): 141–160. doi:10.1016/0377-2217(93)90058-U.

Blazewicz, Jacek, Wolfgang Domschke, and Erwin Pesch. 1996. “The Job Shop Scheduling Problem: Conventional and New Solution Techniques.” *European Journal of Operational Research* 93 (1968): 1–33.

Bok, Jin Kwang, Ignacio E. Grossmann, and Sunwon Park. 2000. "Supply Chain Optimization in Continuous Flexible Process Networks." *Industrial and Engineering Chemistry Research* 39 (5): 1279–1290. doi:10.1021/ie990526w.

Chan, F., S. H. Chung, and P. L.Y. Chan. 2005. "An Adaptive Genetic Algorithm with Dominated Genes for Distributed Scheduling Problems." *Expert Systems with Applications* 29 (2): 364–371. doi:10.1016/j.eswa.2005.04.009.

Chan, Felix T.S., S. H. Chung, L. Y. Chan, Gerd Finke, and M. K. Tiwari. 2006. "Solving Distributed FMS Scheduling Problems Subject to Maintenance: Genetic Algorithms Approach." *Robotics and Computer-Integrated Manufacturing* 22 (5–6): 493–504. doi:10.1016/j.rcim.2005.11.005.

Chan, Felix T.S., S. H. Chung, and P. L.Y. Chan. 2006. "Application of Genetic Algorithms with Dominant Genes in a Distributed Scheduling Problem in Flexible Manufacturing Systems." *International Journal of Production Research* 44 (3): 523–543. doi:10.1080/00207540500319229.

Chan, Felix T.S., Vikas Kumar, and Nishikant Mishra. 2008. "Resolving Multi Plant Supply Chain Problem: A Novel Swarm Intelligence Based Approach." *Proceedings of the 4th IEEE International Conference on Management of Innovation and Technology, ICMIT,* no. Cim: 1066–1071. doi:10.1109/ICMIT.2008.4654516.

Chan, Felix T.S., Anuj Prakash, H. L. Ma, and C. S. Wong. 2013. "A Hybrid Tabu Sample-Sort Simulated Annealing Approach for Solving Distributed Scheduling Problem." *International Journal of Production Research* 51 (9): 2602–2619. doi:10.1080/00207543.2012.737948.

Chan, Felix Tung Sun, and Sai Ho Chung. 2007. "Distributed Scheduling in Multiple-Factory Production with Machine Maintenance." In *Process Planning and Scheduling for Distributed Manufacturing*, 243–267. doi:10.1007/978-1-84628-752-7_10.

Chan, Hing Kai, and Sai Ho Chung. 2013. "Optimisation Approaches for Distributed Scheduling Problems." *International Journal of Production Research* 51 (9): 2571–2577. doi:10.1080/00207543.2012.755345.

Chang, Hao Chin, and Tung Kuan Liu. 2017. "Optimisation of Distributed Manufacturing Flexible Job Shop Scheduling by Using Hybrid Genetic Algorithms." *Journal of Intelligent Manufacturing* 28 (8): 1973–1986. doi:10.1007/s10845-015-1084-y.

Chaouch, Imen, Olfa Belkahla Driss, and Khaled Ghedira. 2017a. "Elitist Ant System for the Distributed Job Shop Scheduling Problem." In *Advances in Artificial Intelligence: From Theory to Practice*, edited by Salem Benferhat, Karim Tabia, and Moonis Ali, 10350:3062–3071. doi:10.1007/978-3-319-60045-1.

Chaouch, Imen, Olfa Belkahla Driss, and Khaled Ghedira. 2017b. "A Modified Ant Colony Optimization Algorithm for the Distributed Job Shop Scheduling Problem." *Procedia Computer Science* 112: 296–305. doi:10.1016/j.procs.2017.08.267.

Chen, Wu Lin, Chin Yin Huang, and Yin Chieh Lai. 2009. "Multi-Tier and Multi-Site Collaborative Production: Illustrated by a Case Example of TFT-LCD Manufacturing." *Computers and Industrial Engineering* 57 (1): 61–72. doi:10.1016/j.cie.2008.08.012.

Chen, Yin Yann. 2014. "The Order Fulfillment Planning Problem Considering Multi-Site Order Allocation and Single-Site Shop Floor Scheduling." *Journal of Intelligent Manufacturing* 25 (3): 441–458. doi:10.1007/s10845-012-0695-9.

Chen, Z-L. 2010. "Integrated Production and Outbound Distribution Scheduling: Review and Extensions." *Operations Research* 58 (1): 130–148. doi:10.1287/opre.1080.0688.

Chen, Z-L., and G. Pundoor. 2006. "Order Assignment and Scheduling in a Supply Chain." *Operations Research* 54 (3): 555–572. doi:10.1287/opre.1060.0280.

Chung, S. H., Felix T.S. Chan, and H. K. Chan. 2009. "A Modified Genetic Algorithm Approach for Scheduling of Perfect Maintenance in Distributed Production Scheduling." *Engineering Applications of Artificial Intelligence* 22 (7): 1005–1014. doi:10.1016/j.engappai.2008.11.004.

Chung, S. H., Felix T.S. Chan, and Wai Hung Ip. 2011. "Minimization of Order Tardiness Through Collaboration Strategy in Multifactory Production System." *IEEE Systems Journal* 5 (1): 40–49.

doi:10.1109/JSYST.2010.2100194.

Chung, S. H., H. C.W. Lau, K. L. Choy, G. T.S. Ho, and Y. K. Tse. 2010. "Application of Genetic Approach for Advanced Planning in Multi-Factory Environment." *International Journal of Production Economics* 127 (2): 300–308. doi:10.1016/j.ijpe.2009.08.019.

Chung, S. H., H. C W Lau, G. T S Ho, and Wai Hung Ip. 2009. "Optimization of System Reliability in Multi-Factory Production Networks by Maintenance Approach." *Expert Systems with Applications* 36 (6): 10188–10196. doi:10.1016/j.eswa.2008.12.014.

Cicirello, Vincent A., and Stephen F. Smith. 2004. "Wasp-like Agents for Distributed Factory Coordination." *Autonomous Agents and Multi-Agent Systems* 8 (3): 237–266. doi:10.1023/B:AGNT.0000018807.12771.60.

Cóccola, M. E., M. Zamarripa, C. A. Méndez, and A. Espuña. 2013. "Toward Integrated Production and Distribution Management in Multi-Echelon Supply Chains." *Computers and Chemical Engineering* 57: 78–94. doi:10.1016/j.compchemeng.2013.01.004.

Companys, Ramon, and Imma Ribas. 2016. "Efficient Constructive Procedures for the Distributed Blocking Flow Shop Scheduling Problem." In *Proceedings of 2015 International Conference on Industrial Engineering and Systems Management, IEEE IESM 2015*, 92–98. doi:10.1109/IESM.2015.7380142.

Cooper, Harris M. 1988. "Organizing Knowledge Syntheses: A Taxonomy of Literature Reviews." *Knowledge in Society* 1 (1): 104–126. doi:10.1007/BF03177550.

Copil, Karina, Martin Wörbelauer, Herbert Meyr, and Horst Tempelmeier. 2017. "Simultaneous Lotsizing and Scheduling Problems: A Classification and Review of Models." *OR Spectrum* 39 (1): 1–64. doi:10.1007/s00291-015-0429-4.

De Giovanni, L., and F. Pezzella. 2010. "An Improved Genetic Algorithm for the Distributed and Flexible Job-Shop Scheduling Problem." *European Journal of Operational Research* 200 (2): 395–408. doi:10.1016/j.ejor.2009.01.008.

De Matta, Renato, and Tan Miller. 2004. "Production and Inter-Facility Transportation Scheduling for a Process Industry." *European Journal of Operational Research* 158 (1): 72–88. doi:10.1016/S0377-2217(03)00358-8.

Dempster, Paul, Penghao Li, and John H. Drake. 2017. "Solving the Distributed Two Machine Flow-Shop Scheduling Problem Using Differential Evolution." *Lecture Notes in Computer Science* 10385 LNCS: 449–457. doi:10.1007/978-3-319-61824-1_49.

Deng, Jin, Ling Wang, Jingnan Shen, and Xiaolong Zheng. 2016. "An Improved Harmony Search Algorithm for the Distributed Two Machine Flow-Shop Scheduling Problem." In *Harmony Search Algorithm -Proceedings of the 2nd International Conference on Harmony Search Algorithm (ICHSA 2015)*, edited by Joong Hoon Kim and Zong Woo Geem, 382:269–278. Advances in Intelligent Systems and Computing. doi:10.1007/978-3-662-47926-1.

Deng, Jin, Ling Wang, Sheng Yao Wang, and Xiao Long Zheng. 2016. "A Competitive Memetic Algorithm for the Distributed Two-Stage Assembly Flow-Shop Scheduling Problem." *International Journal of Production Research* 54 (12): 3561–3577. doi:https://doi.org/10.1016/j.swevo.2016.06.002.

Dolgui, Alexandre, Dmitry Ivanov, Semyon Potryasaev, Boris Sokolov, Marina Ivanova, and Frank Werner. 2020. "Blockchain-Oriented Dynamic Modelling of Smart Contract Design and Execution in the Supply Chain." *International Journal of Production Research* 58 (7): 2184–2199. doi:10.1080/00207543.2019.1627439.

Durach, Christian F., Joakim Kembro, and Andreas Wieland. 2017. "A New Paradigm for Systematic Literature Reviews in Supply Chain Management." *Journal of Supply Chain Management* 53 (4): 67–85. doi:10.1111/jscm.12145.

Feng, Pingping, Ya Liu, Feng Wu, and Chengbin Chu. 2017. "Two Heuristics for Coordinating Production Planning and Transportation Planning." *International Journal of Production Research* 7543: 1–18. doi:10.1080/00207543.2017.1351631.

Fernandez-Viagas, Victor, and Jose M. Framinan. 2015. "A Bounded-Search Iterated Greedy Algorithm for the Distributed Permutation Flowshop Scheduling Problem." *International Journal of Production Research* 53 (4): 1111–1123. doi:10.1080/00207543.2014.948578.

Fernandez-Viagas, Victor, Paz Perez-Gonzalez, and Jose M. Framinan. 2018. "The Distributed Permutation Flow Shop to Minimise the Total Flowtime." *Computers and Industrial Engineering* 118 (August 2017): 464–477. doi:10.1016/j.cie.2018.03.014.

Fink, Arlene. 2013. *Conducting Research Literature Reviews: From the Internet to Paper*. 4th edition. Los Angeles: SAGE Publications.

Fu, Liang Liang, Mohamed Ali Aloulou, and Chefi Triki. 2017. "Integrated Production Scheduling and Vehicle Routing Problem with Job Splitting and Delivery Time Windows." *International Journal of Production Research* 55 (20): 5942–5957. doi:10.1080/00207543.2017.1308572.

Gao, Jian, and Rong Chen. 2011. "A Hybrid Genetic Algorithm for the Distributed Permutation Flowshop Scheduling Problem." *International Journal of Computational Intelligence Systems* 4 (4): 497–508. doi:10.1080/18756891.2011.9727808.

Gao, Jian, Rong Chen, and Wu Deng. 2013. "An Efficient Tabu Search Algorithm for the Distributed Permutation Flowshop Scheduling Problem." *International Journal of Production Research* 51 (3): 641–651. doi:10.1080/00207543.2011.644819.

Garcia, J. M., S. Lozano, and D. Canca. 2004. "Coordinated Scheduling of Production and Delivery from Multiple Plants." *Robotics and Computer-Integrated Manufacturing* 20 (3): 191–198. doi:10.1016/j.rcim.2003.10.004.

Garey, M., and D. Johnson. 1979. *Computers and Intractability: A Guide to the Theory of NP-Completeness*. US: W. H. Freeman and Company.

Gascon, André, Pierre Lefrançois, and Louis Cloutier. 1998. "Computer-Assisted Multi-Item, Multi-Machine and Multi-Site Scheduling in a Hardwood Flooring Factory." *Computers in Industry* 36 (3): 231–244. doi:10.1016/S0166-3615(98)00074-8.

Gnoni, M. G., R. Iavagnilio, G. Mossa, G. Mummolo, and A. Di Leva. 2003. "Production Planning of a Multi-Site Manufacturing System by Hybrid Modelling: A Case Study from the Automotive Industry." *International Journal of Production Economics* 85 (2): 251–262. doi:10.1016/S0925-5273(03)00113-0.

Gonzalez-Neira, Eliana Maria, Daniele Ferone, Sara Hatami, and Angel A. Juan. 2017. "A Biased-Randomized Simheuristic for the Distributed Assembly Permutation Flowshop Problem with Stochastic Processing Times." *Simulation Modelling Practice and Theory* 79 (December): 23–36. doi:10.1016/j.simpat.2017.09.001.

Graham, R. L., Lawler, E. L., Lenstra, J. K. and Rinnooy Kan, A. H. G. 1979. "Optimization and Approximation in Deterministic Sequencing and Scheduling: A Survey." *Annals of Discrete Mathematics* 5: 287–326. doi:10.1016/S0167-5060(08)70356-X.

Guinet, Alain. 2001. "Multi-Site Planning: A Transshipment Problem." *International Journal of Production Economics* 74 (1–3): 21–32. doi:10.1016/S0925-5273(01)00104-9.

Guo, Z. X., W. K. Wong, Zhi Li, and Peiyu Ren. 2013. "Modeling and Pareto Optimization of Multi-Objective Order Scheduling Problems in Production Planning." *Computers and Industrial Engineering* 64 (4): 972–986. doi:10.1016/j.cie.2013.01.006.

Guo, Z. X., Can Yang, Wei Wang, and Jing Yang. 2015. "Harmony Search-Based Multi-Objective Optimization Model for Multi-Site Order Planning with Multiple Uncertainties and Learning Effects." *Computers and Industrial Engineering* 83: 74–90. doi:10.1016/j.cie.2015.01.023.

H'Mida, Fehmi, and Pierre Lopez. 2013. "Multi-Site Scheduling under Production and Transportation Constraints." *International Journal of Computer Integrated Manufacturing* 26 (3): 252–266. doi:10.1080/0951192X.2012.688141.

Hao, Jian-hua, Jun-qing Li, Yu Du, Mei-xian Song, Peng Duan, and Ying-yu Zhang. 2019. "Solving Distributed Hybrid Flowshop Scheduling Problems by a Hybrid Brain Storm Optimization Algorithm." *IEEE Access* 7: 1–1. doi:10.1109/access.2019.2917273.

Harjunkoski, Iiro, Christos T. Maravelias, Peter Bongers, Pedro M. Castro, Sebastian Engell, Ignacio E. Grossmann, John Hooker, Carlos Méndez, Guido Sand, and John Wassick. 2014. "Scope for Industrial Applications of Production Scheduling Models and Solution Methods." *Computers and Chemical Engineering* 62: 161–193. doi:10.1016/j.compchemeng.2013.12.001.

Hatami, Sara, Laura Calvet, Victor Fernández-Viagas, Jose M. Framinan, and Angel A. Juan. 2018. "A Simheuristic Algorithm to Set up Starting Times in the Stochastic Parallel Flowshop Problem." *Simulation Modelling Practice and Theory* 86 (February): 55–71. doi:10.1016/j.simpat.2018.04.005.

Hatami, Sara, Rubén Ruiz, and Carlos Andrés-Romano. 2013. "The Distributed Assembly Permutation Flowshop Scheduling Problem." *International Journal of Production Research* 51 (17): 5292–5308. doi:10.1080/00207543.2013.807955.

Hatami, Sara, Rubén Ruiz, and Carlos Andrés-Romano. 2015. "Heuristics and Metaheuristics for the Distributed Assembly Permutation Flowshop Scheduling Problem with Sequence Dependent Setup Times." *International Journal of Production Economics* 169: 76–88. doi:10.1016/j.ijpe.2015.07.027.

Hosseini, Behnaz, and Barış Tan. 2019. "Modelling and Analysis of a Cooperative Production Network." *International Journal of Production Research* 57 (21): 6665–6686. doi:10.1080/00207543.2019.1571254.

Ivanov, Dmitry, Alexandre Dolgui, and Boris Sokolov. 2019. "The Impact of Digital Technology and Industry 4.0 on the Ripple Effect and Supply Chain Risk Analytics." *International Journal of Production Research* 57 (3): 829–846. doi:10.1080/00207543.2018.1488086.

Jackson, James R. 1955. "Scheduling a Production Line to Minimize Maximum Tardiness." *Management Science Research Project, University of California, Los Angeles*, 72.

Jackson, James R. 1956. "An Extension of Johnson's Results on Job IDT Scheduling." *Naval Research Logistics Quarterly* 3 (3): 201–203. doi:10.1002/nav.3800030307.

Jacobs, Larry W., and Michael J. Brusco. 1995. "Note: A Local-search Heuristic for Large Set-covering Problems." *Naval Research Logistics* 42 (7): 1129–1140.

Ji, Mengchen, Yixin Yang, Wenzhe Duan, Shouyang Wang, and Bo Liu. 2016. "Scheduling of No-Wait Stochastic Distributed Assembly Flowshop by Hybrid PSO." *2016 IEEE Congress on Evolutionary Computation, CEC 2016*, no. 71101139: 2649–2654. doi:10.1109/CEC.2016.7744120.

Jia, H. Z., J. Y.H. Fuh, A. Y.C. Nee, and Y. F. Zhang. 2002. "Web-Based Multi-Functional Scheduling System for a Distributed Manufacturing Environment." *Concurrent Engineering Research and Applications* 10 (1): 27–39. doi:10.1177/1063293X02010001054.

Jia, H. Z., J. Y.H. Fuh, A. Y.C. Nee, and Y. F. Zhang. 2007. "Integration of Genetic Algorithm and Gantt Chart for Job Shop Scheduling in Distributed Manufacturing Systems." *Computers and Industrial Engineering* 53 (2): 313–320. doi:10.1016/j.cie.2007.06.024.

Jia, H. Z., A. Y.C. Nee, J. Y.H. Fuh, and Y. F. Zhang. 2003. "A Modified Genetic Algorithm for Distributed Scheduling Problems." *Journal of Intelligent Manufacturing* 14 (3–4): 351–362. doi:10.1023/A:1024653810491.

Kanyalkar, A. P., and G. K. Adil. 2005. "An Integrated Aggregate and Detailed Planning in a Multi-Site Production Environment Using Linear Programming." *International Journal of Production Research* 43 (20): 4431–4454. doi:10.1080/00207540500142332.

Karageorgos, Anthony, Nikolay Mehandjiev, Georg Weichhart, and Alexander Hämmerle. 2003. "Agent-Based Optimisation of Logistics and Production Planning." In *Engineering Applications of Artificial Intelligence*, 16:335–348. doi:10.1016/S0952-1976(03)00076-9.

Karimi, N., and H. Davoudpour. 2015. "A Branch and Bound Method for Solving Multi-Factory Supply Chain Scheduling with Batch Delivery." *Expert Systems with Applications* 42 (1): 238–245. doi:10.1016/j.eswa.2014.07.025.

Karimi, N., and H. Davoudpour. 2017a. "Integrated Production and Delivery Scheduling for Multi-Factory Supply Chain with Stage-Dependent Inventory Holding Cost." *Computational and Applied Mathematics* 36 (4): 1529–1544. doi:10.1007/s40314-016-0305-0.

Karimi, N., and H. Davoudpour. 2017b. “A Knowledge-Based Approach for Multi-Factory Production Systems.” *Computers and Operations Research* 77: 72–85. doi:10.1016/j.cor.2016.07.003.

Kerkhove, Louis Philippe, and Mario Vanhoucke. 2014. “Scheduling of Unrelated Parallel Machines with Limited Server Availability on Multiple Production Locations: A Case Study in Knitted Fabrics.” *International Journal of Production Research* 52 (9): 2630–2653. doi:10.1080/00207543.2013.865855.

Komaki, G. M., and B. Malakooti. 2017. “General Variable Neighborhood Search Algorithm to Minimize Makespan of the Distributed No-Wait Flow Shop Scheduling Problem.” *Production Engineering* 11 (3): 315–329. doi:10.1007/s11740-017-0716-9.

Kopanos, Georgios M., and Luis Puigjaner. 2009. *Multi-Site Scheduling/Batching and Production Planning for Batch Process Industries*. *Computer Aided Chemical Engineering*. Vol. 27. doi:10.1016/S1570-7946(09)70742-4.

Kriett, Phillip O., Sebastian Eirich, and Martin Grunow. 2017. “Cycle Time-Oriented Mid-Term Production Planning for Semiconductor Wafer Fabrication.” *International Journal of Production Research* 55 (16): 4662–4679. doi:10.1080/00207543.2016.1278083.

Lau, Jason, George Q. Huang, L. Liang, and K. L. Mak. 2006. “Agent-Based Modeling of Supply Chains for Distributed Scheduling.” *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans* 36 (5): 847–861. doi:10.1109/TSMCA.2005.854231.

Lawrynowicz, Anna. 2011. “Advanced Scheduling with Genetic Algorithms in Supply Networks.” *Journal of Manufacturing Technology Management* 22 (6): 748–769. doi:10.1108/17410381111149620.

Lei, Deming, Yue Yuan, Jingcao Cai, and Danyu Bai. 2019. “An Imperialist Competitive Algorithm with Memory for Distributed Unrelated Parallel Machines Scheduling.” *International Journal of Production Research* 0 (0): 1–18. doi:10.1080/00207543.2019.1598596.

Leng, Jiewu, and Pingyu Jiang. 2019. “Dynamic Scheduling in RFID-Driven Discrete Manufacturing System by Using Multi-Layer Network Metrics as Heuristic Information.” *Journal of Intelligent Manufacturing* 30 (3): 979–994. doi:10.1007/s10845-017-1301-y.

Leng, Jiewu, Pingyu Jiang, Kailin Xu, Qiang Liu, J. Leon Zhao, Yiyang Bian, and Rui Shi. 2019. “Makerchain: A Blockchain with Chemical Signature for Self-Organizing Process in Social Manufacturing.” *Journal of Cleaner Production* 234: 767–778. doi:10.1016/j.jclepro.2019.06.265.

Leng, Jiewu, Douxi Yan, Qiang Liu, Kailin Xu, J. Leon Zhao, Rui Shi, Lijun Wei, Ding Zhang, and Xin Chen. 2019. “ManuChain: Combining Permissioned Blockchain With a Holistic Optimization Model as Bi-Level Intelligence for Smart Manufacturing.” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 1–11. doi:10.1109/tsmc.2019.2930418.

Li, Chung Lun, and Jinwen Ou. 2007. “Coordinated Scheduling of Customer Orders with Decentralized Machine Locations.” *IIE Transactions (Institute of Industrial Engineers)* 39 (9): 899–909. doi:10.1080/07408170600972990.

Li, Xiangtao, Xin Zhang, Minghao Yin, and Jianan Wang. 2015. “A Genetic Algorithm for the Distributed Assembly Permutation Flowshop Scheduling Problem.” In *2015 IEEE Congress on Evolutionary Computation, CEC 2015 - Proceedings*, 3096–3101. doi:10.1109/CEC.2015.7257275.

Li, Zhengyang, Wenzhe Duan, Mengchen Ji, Yixin Yang, Shouyang Wang, and Bo Liu. 2016. “The Distributed Permutation Flowshop Scheduling Problem with Different Transport Timetables and Loading Capacities.” *2016 IEEE Congress on Evolutionary Computation, CEC 2016*, no. 71101139: 2433–2437. doi:10.1109/CEC.2016.7744090.

Lim, Ming K., Kim Tan, and Stephen C.H. Leung. 2013. “Using a Multi-Agent System to Optimise Resource Utilisation in Multi-Site Manufacturing Facilities.” *International Journal of Production Research* 51 (9): 2620–2638. doi:10.1080/00207543.2012.737953.

Lin, James T., and Yin Yann Chen. 2007. “A Multi-Site Supply Network Planning Problem Considering Variable Time Buckets- A TFT-LCD Industry Case.” *International Journal of Advanced Manufacturing Technology* 33 (9–10): 1031–1044. doi:10.1007/s00170-006-0537-z.

Lin, Jian, Zhou Jing Wang, and Xiaodong Li. 2017. “A Backtracking Search Hyper-Heuristic for the

Distributed Assembly Flow-Shop Scheduling Problem." *Swarm and Evolutionary Computation* 36 (April): 124–135. doi:10.1016/j.swevo.2017.04.007.

Lin, Jian, and Shuai Zhang. 2016. "An Effective Hybrid Biogeography-Based Optimization Algorithm for the Distributed Assembly Permutation Flow-Shop Scheduling Problem." *Computers and Industrial Engineering* 97: 128–136. doi:10.1016/j.cie.2016.05.005.

Lin, Shih Wei, and Kuo Ching Ying. 2016. "Minimizing Makespan for Solving the Distributed No-Wait Flowshop Scheduling Problem." *Computers and Industrial Engineering* 99: 202–209. doi:10.1016/j.cie.2016.07.027.

Lin, Shih Wei, Kuo Ching Ying, and Chien Yi Huang. 2013. "Minimising Makespan in Distributed Permutation Flowshops Using a Modified Iterated Greedy Algorithm." *International Journal of Production Research* 51 (16): 5029–5038. doi:10.1080/00207543.2013.790571.

Liu, Hongcheng, and Liang Gao. 2010. "A Discrete Electromagnetism-like Mechanism Algorithm for Solving Distributed Permutation Flowshop Scheduling Problem." In *Proceedings - 2010 International Conference on Manufacturing Automation, ICMA 2010*, 156–163. doi:10.1109/ICMA.2010.17.

Liu, Tung-Kuan, Yeh-Peng Chen, and Jyh-Horng Chou. 2015. "Solving Distributed and Flexible Job-Shop Scheduling Problems for a Real-World Fastener Manufacturer." *IEEE Access* 2: 1598–1606. doi:10.1109/access.2015.2388486.

Liu, Yongkui, Lihui Wang, Xi Vincent Wang, Xun Xu, and Lin Zhang. 2018. "Scheduling in Cloud Manufacturing: State-of-the-Art and Research Challenges." *International Journal of Production Research* 7543: 1–26. doi:10.1080/00207543.2018.1449978.

Lohmer, Jacob. 2019. "Applicability of Blockchain Technology in Scheduling Resources Within Distributed Manufacturing." In *Logistics Management - Proceedings of the German Academic Association for Business Research 2019*, 89–103. doi:10.1007/978-3-030-29821-0_7.

Lou, P., S. K. Ong, and A. Y.C. Nee. 2010. "Agent-Based Distributed Scheduling for Virtual Job Shops." *International Journal of Production Research* 48 (13): 3889–3910. doi:10.1080/00207540902927918.

Lu, Po-Hsiang, Muh-Cherng Wu, Hao Tan, Yong-Han Peng, and Chen-Fu Chen. 2015. "A Genetic Algorithm Embedded with a Concise Chromosome Representation for Distributed and Flexible Job-Shop Scheduling Problems." *Journal of Intelligent Manufacturing* 29 (1): 19–34. doi:10.1007/s10845-015-1083-z.

Mack, Oliver, Anshuman Khare, Andreas Krämer, and Thomas Burgartz. 2015. *Managing in a VUCA World*. Springer Cham Switzerland. doi:10.1007/978-3-319-16889-0.

Marandi, Fateme, and S. M.T. Fatemi Ghomi. 2019. "Integrated Multi-Factory Production and Distribution Scheduling Applying Vehicle Routing Approach." *International Journal of Production Research* 57 (3): 722–748. doi:10.1080/00207543.2018.1481301.

Marzouki, Bilel, Olfa Belkahla Driss, and Khaled Ghedira. 2018. "Decentralized Tabu Searches in Multi Agent System for Distributed and Flexible Job Shop Scheduling Problem." *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, AICCSA* 2017-Octob: 1019–1026. doi:10.1109/AICCSA.2017.133.

Miller, Tan, and Renato De Matta. 2003. "Integrating Production and Transportation Scheduling Decisions Between Two Geographically Separated Plants." *Journal of Business Logistics* 24 (1): 111–146. doi:10.1002/j.2158-1592.2003.tb00034.x.

Moon, Chiung, Jongsoo Kim, and Sun Hur. 2002. "Integrated Process Planning and Scheduling with Minimizing Total Tardiness in Multi-Plants Supply Chain." *Computers and Industrial Engineering* 43 (1–2): 331–349. doi:10.1016/S0360-8352(02)00078-5.

Moon, Chiung, and Yoonho Seo. 2005a. "Evolutionary Algorithm for Advanced Process Planning and Scheduling in a Multi-Plant." *Computers and Industrial Engineering* 48 (2): 311–325. doi:10.1016/j.cie.2005.01.016.

Moon, Chiung, and Yoonho Seo. 2005b. "Advanced Planning for Minimizing Makespan with Load

Balancing in Multi-Plant Chain." *International Journal of Production Research* 43 (20): 4381–4396. doi:10.1080/00207540500142449.

Moon, Chiung, Yoonho Seo, Youngsu Yun, and Mitsuo Gen. 2006. "Adaptive Genetic Algorithm for Advanced Planning in Manufacturing Supply Chain." *Journal of Intelligent Manufacturing* 17 (4): 509–522. doi:10.1007/s10845-005-0010-0.

Naderi, Bahman, and Ahmed Azab. 2014. "Modeling and Heuristics for Scheduling of Distributed Job Shops." *Expert Systems with Applications* 41 (17): 7754–7763. doi:10.1016/j.eswa.2014.06.023.

Naderi, Bahman, and Ahmed Azab. 2015. "An Improved Model and Novel Simulated Annealing for Distributed Job Shop Problems." *International Journal of Advanced Manufacturing Technology* 81 (1–4): 693–703. doi:10.1007/s00170-015-7080-8.

Naderi, Bahman, and Rubén Ruiz. 2010. "The Distributed Permutation Flowshop Scheduling Problem." *Computers and Operations Research* 37 (4): 754–768. doi:10.1016/j.cor.2009.06.019.

Naderi, Bahman, and Rubén Ruiz. 2014. "A Scatter Search Algorithm for the Distributed Permutation Flowshop Scheduling Problem." *European Journal of Operational Research* 239 (2): 323–334. doi:10.1016/j.ejor.2014.05.024.

Naso, David, Michele Surico, Biagio Turchiano, and Uzay Kaymak. 2007. "Genetic Algorithms for Supply-Chain Scheduling: A Case Study in the Distribution of Ready-Mixed Concrete." *European Journal of Operational Research* 177 (3): 2069–2099. doi:10.1016/j.ejor.2005.12.019.

Nawaz, Muhammad, E. Emory Enscore, and Inyong Ham. 1983. "A Heuristic Algorithm for the M-Machine, n-Job Flow-Shop Sequencing Problem." *Omega* 11 (1): 91–95. doi:10.1016/0305-0483(83)90088-9.

Nigro, G., S. Noto La Diega, G. Perrone, and P. Renna. 2003. "Coordination Policies to Support Decision Making in Distributed Production Planning." *Robotics and Computer-Integrated Manufacturing* 19 (6): 521–531. doi:10.1016/S0736-5845(03)00062-0.

Olhager, Jan, and Andreas Feldmann. 2018. "Distribution of Manufacturing Strategy Decision-Making in Multi-Plant Networks." *International Journal of Production Research* 56 (1–2): 692–708. doi:10.1080/00207543.2017.1401749.

Ouelhadj, Djamila, and Sanja Petrovic. 2009. "A Survey of Dynamic Scheduling in Manufacturing Systems." *Journal of Scheduling* 12 (4): 417–431. doi:10.1007/s10951-008-0090-8.

Pan, Quan-Ke, Liang Gao, Ling Wang, Jing Liang, and Xin-Yu Li. 2019. "Effective Heuristics and Metaheuristics to Minimize Total Flowtime for the Distributed Permutation Flowshop Problem." *Expert Systems with Applications* 124 (June): 309–324. doi:10.1016/j.eswa.2019.01.062.

Pan, Quan-Ke, Liang Gao, Li Xin-Yu, and Jose M. Framinan. 2019. "Effective Constructive Heuristics and Meta-Heuristics for the Distributed Assembly Permutation Flowshop Scheduling Problem." *Applied Soft Computing* 81: 105492. doi:10.1016/j.asoc.2019.105492.

Parente, Manuel, Gonçalo Figueira, Pedro Amorim, and Alexandra Marques. 2020. "Production Scheduling in the Context of Industry 4.0: Review and Trends." *International Journal of Production Research* 7543 (February): 1–31. doi:10.1080/00207543.2020.1718794.

Pinedo, Michael. 2014. *Scheduling - Theory, Algorithms, and Systems*. 4th edition. New York: Springer.

Ribas, Imma, Ramon Companys, and Xavier Tort-Martorell. 2017. "Efficient Heuristics for the Parallel Blocking Flow Shop Scheduling Problem." *Expert Systems with Applications* 74: 41–54. doi:10.1016/j.eswa.2017.01.006.

Rifai, Achmad P., Huu-Tho Nguyen, and Siti Zawiah Md Dawal. 2016. "Multi-Objective Adaptive Large Neighborhood Search for Distributed Reentrant Permutation Flow Shop Scheduling." *Applied Soft Computing* 40 (March): 42–57. doi:10.1016/j.asoc.2015.11.034.

Rossit, Daniel Alejandro, Fernando Tohmé, and Mariano Frutos. 2018. "The Non-Permutation Flow-Shop Scheduling Problem: A Literature Review." *Omega (United Kingdom)* 77: 143–153. doi:10.1016/j.omega.2017.05.010.

Rossit, Daniel Alejandro, Fernando Tohmé, and Mariano Frutos. 2019. "Industry 4.0: Smart Scheduling."

International Journal of Production Research 57 (12): 3802–3813. doi:10.1080/00207543.2018.1504248.

Ruifeng, Chen, and Velusamy Subramaniam. 2011. “Performance Evaluation for Tandem Multi-Factory Supply Chains: An Approximate Solution.” *International Journal of Production Research* 49 (11): 3285–3305. doi:10.1080/00207541003792243.

Ruiz, Rubén, Quan-Ke Pan, and Bahman Naderi. 2019. “Iterated Greedy Methods for the Distributed Permutation Flowshop Scheduling Problem.” *Omega* 83 (March): 213–222. doi:10.1016/j.omega.2018.03.004.

Sauer, Jürgen. 1998. “A Multi-Site Scheduling System.” In *Proceedings of the Artificial Intelligence and Manufacturing Workshop*, 161–168.

Shah, Nikisha K., and Marianthi G. Ierapetritou. 2012. “Integrated Production Planning and Scheduling Optimization of Multisite, Multiproduct Process Industry.” *Computers and Chemical Engineering* 37: 214–226. doi:10.1016/j.compchemeng.2011.08.007.

Shao, Weishi, Dechang Pi, and Zhongshi Shao. 2017a. “A Hybrid Iterated Greedy Algorithm for the Distributed No-Wait Flow Shop Scheduling Problem.” In *2017 IEEE Congress on Evolutionary Computation, CEC 2017 - Proceedings*, 9–16. doi:10.1109/CEC.2017.7969289.

Shao, Weishi, Dechang Pi, and Zhongshi Shao. 2017b. “Optimization of Makespan for the Distributed No-Wait Flow Shop Scheduling Problem with Iterated Greedy Algorithms.” *Knowledge-Based Systems* 137: 163–181. doi:10.1016/j.knosys.2017.09.026.

Sun, X. T., S. H. Chung, and Felix T.S. Chan. 2015. “Integrated Scheduling of a Multi-Product Multi-Factory Manufacturing System with Maritime Transport Limits.” *Transportation Research Part E: Logistics and Transportation Review* 79: 110–127. doi:10.1016/j.tre.2015.04.002.

Taillard, E. 1990. “Some Efficient Heuristic Methods for the Flow Shop Sequencing Problem.” *European Journal of Operational Research* 47 (1): 65–74. doi:10.1016/0377-2217(90)90090-X.

Talbi, El-Ghazali. 2009. *Metaheuristics*. *Metaheuristics: From Design to Implementation*. doi:10.1002/9780470496916.

Terrazas-Moreno, Sebastian, and Ignacio E. Grossmann. 2011. “A Multiscale Decomposition Method for the Optimal Planning and Scheduling of Multi-Site Continuous Multiproduct Plants.” *Chemical Engineering Science* 66 (19): 4307–4318. doi:10.1016/j.ces.2011.03.017.

Thomé, Antônio Márcio Tavares, Luiz Felipe Scavarda, and Annibal José Scavarda. 2016. “Conducting Systematic Literature Review in Operations Management.” *Production Planning and Control* 27 (5): 408–420. doi:10.1080/09537287.2015.1129464.

Thoney, Kristin A., Thom J. Hodgson, Russell E. King, Mehmet R. Taner, and Amy D. Wilson. 2002. “Satisfying Due-Dates in Large Multi-Factory Supply Chains.” *IIE Transactions* 34 (9): 803–811. doi:10.1023/A:1015500822105.

Toptal, Aysegul, and Ihsan Sabuncuoglu. 2010. “Distributed Scheduling: A Review of Concepts and Applications.” *International Journal of Production Research* 48 (18): 5235–5262. doi:10.1080/00207540903121065.

Tranfield, David, David Denyer, and Palminder Smart. 2003. “Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review.” *British Journal of Management* 14 (3): 207–222. doi:10.1111/1467-8551.00375.

Tsai, Kune m., and Shan c. Wang. 2009. “Multi-Site Available-to-Promise Modeling for Assemble-to-Order Manufacturing: An Illustration on TFT-LCD Manufacturing.” *International Journal of Production Economics* 117 (1): 174–184. doi:10.1016/j.ijpe.2008.10.010.

Tukamuhabwa, Benjamin R., Mark Stevenson, Jerry Busby, and Marta Zorzini. 2015. “Supply Chain Resilience: Definition, Review and Theoretical Foundations for Further Study.” *International Journal of Production Research* 53 (18): 5592–5623. doi:10.1080/00207543.2015.1037934.

Vom Brocke, Jan, Alexander Simons, Bjoern Niehaves, and Kai Reimer. 2009. “Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process.” In *European*

Conference on Information Systems (ECIS), 2206–2217. http://link.springer.com/10.1007/BF01938871.

Wang, Jing Jing, and Ling Wang. 2018. "A Knowledge-Based Cooperative Algorithm for Energy-Efficient Scheduling of Distributed Flow-Shop." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 2018-Janua: 1–15. doi:10.1109/TSMC.2017.2788879.

Wang, Jingjing, Ling Wang, and Jingnan Shen. 2016. "A Hybrid Discrete Cuckoo Search for Distributed Permutation Flowshop Scheduling Problem." In *2016 IEEE Congress on Evolutionary Computation, CEC 2016*, 2240–2246. doi:10.1109/CEC.2016.7744065.

Wang, Kai, Yun Huang, and Hu Qin. 2016. "A Fuzzy Logic-Based Hybrid Estimation of Distribution Algorithm for Distributed Permutation Flowshop Scheduling Problems under Machine Breakdown." *Journal of the Operational Research Society* 67 (1): 68–82. doi:10.1057/jors.2015.50.

Wang, Peng-Sen, Taho Yang, and Liang-Chiuan Yu. 2018. "Lean-Pull Strategy for Order Scheduling Problem in a Multi-Site Semiconductor Crystal Ingot-Pulling Manufacturing Company." *Computers & Industrial Engineering* 125 (November): 545–562. doi:10.1016/j.cie.2018.03.043.

Wang, Sheng Yao, and Ling Wang. 2016. "An Estimation of Distribution Algorithm-Based Memetic Algorithm for the Distributed Assembly Permutation Flow-Shop Scheduling Problem." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 46 (1): 139–149. doi:10.1109/TSMC.2015.2416127.

Wang, Sheng Yao, Ling Wang, Min Liu, and Ye Xu. 2013. "An Effective Estimation of Distribution Algorithm for Solving the Distributed Permutation Flow-Shop Scheduling Problem." *International Journal of Production Economics* 145 (1): 387–396. doi:10.1016/j.ijpe.2013.05.004.

Wu, Muh Cherng, Chi Shiuan Lin, Chia Hui Lin, and Chen Fu Chen. 2017. "Effects of Different Chromosome Representations in Developing Genetic Algorithms to Solve DFJS Scheduling Problems." *Computers and Operations Research* 80: 101–112. doi:10.1016/j.cor.2016.11.021.

Xiong, Fuli, and Keyi Xing. 2014. "Meta-Heuristics for the Distributed Two-Stage Assembly Scheduling Problem with Bi-Criteria of Makespan and Mean Completion Time." *International Journal of Production Research* 52 (9): 2743–2766. doi:10.1080/00207543.2014.884290.

Xiong, Fuli, Keyi Xing, Feng Wang, Hang Lei, and Libin Han. 2014. "Minimizing the Total Completion Time in a Distributed Two Stage Assembly System with Setup Times." *Computers and Operations Research* 47: 92–105. doi:10.1016/j.cor.2014.02.005.

Xu, Chaojun, Guido Sand, and Sebastian Engell. 2010. *Coordination of Distributed Production Planning and Scheduling Systems*. *IFAC Proceedings Volumes (IFAC-PapersOnline)*. Vol. 43. doi:10.3182/20100908-3-PT-3007.00026.

Xu, Ye, Ling Wang, Shengyao Wang, and Min Liu. 2014. "An Effective Hybrid Immune Algorithm for Solving the Distributed Permutation Flow-Shop Scheduling Problem." *Engineering Optimization* 46 (9): 1269–1283. doi:10.1080/0305215X.2013.827673.

Yazdani, M., Sheida Gohari, and Bahman Naderi. 2015. "Multi-Factory Parallel Machine Problems: Improved Mathematical Models and Artificial Bee Colony Algorithm." *Computers and Industrial Engineering* 81: 36–45. doi:10.1016/j.cie.2014.12.023.

Ying, Kuo Ching, and Shih Wei Lin. 2017. "Minimizing Makespan in Distributed Blocking Flowshops Using Hybrid Iterated Greedy Algorithms." *IEEE Access* 5: 15694–15705. doi:10.1109/ACCESS.2017.2732738.

Ying, Kuo Ching, and Shih Wei Lin. 2018. "Minimizing Makespan for the Distributed Hybrid Flowshop Scheduling Problem with Multiprocessor Tasks." *Expert Systems with Applications* 92: 132–141. doi:10.1016/j.eswa.2017.09.032.

Ying, Kuo Ching, Shih Wei Lin, Chen Yang Cheng, and Cheng Ding He. 2017. "Iterated Reference Greedy Algorithm for Solving Distributed No-Idle Permutation Flowshop Scheduling Problems." *Computers and Industrial Engineering* 110: 413–423. doi:10.1016/j.cie.2017.06.025.

Zhang, Guanghui, and Keyi Xing. 2018. "Memetic Social Spider Optimization Algorithm for Scheduling Two-Stage Assembly Flowshop in a Distributed Environment." *Computers and Industrial*

Engineering 125 (28): 423–433. doi:10.1016/j.cie.2018.09.007.

Zhang, Guanghui, Keyi Xing, and Feng Cao. 2018a. "Discrete Differential Evolution Algorithm for Distributed Blocking Flowshop Scheduling with Makespan Criterion." *Engineering Applications of Artificial Intelligence* 76 (28): 96–107. doi:10.1016/j.engappai.2018.09.005.

Zhang, Guanghui, Keyi Xing, and Feng Cao. 2018b. "Scheduling Distributed Flowshops with Flexible Assembly and Set-up Time to Minimise Makespan." *International Journal of Production Research* 56 (9): 3226–3244. doi:10.1080/00207543.2017.1401241.

Ziaee, Mohsen. 2014. "A Heuristic Algorithm for the Distributed and Flexible Job-Shop Scheduling Problem." *Journal of Supercomputing* 67 (1): 69–83. doi:10.1007/s11227-013-0986-8.