TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 05/15 pp625–645
DOI: 10.26599/TST.2021.9010009
Volume 26, Number 5, October 2021

Distributed Scheduling Problems in Intelligent Manufacturing Systems

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Abstract: Currently, manufacturing enterprises face increasingly fierce market competition due to the various demands of customers and the rapid development of economic globalization. Hence, they have to extend their production mode into distributed environments and establish multiple factories in various geographical locations. Nowadays, distributed manufacturing systems have been widely adopted in industrial production processes. In recent years, many studies have been done on the modeling and optimization of distributed scheduling problems. This work provides a literature review on distributed scheduling problems in intelligent manufacturing systems. By summarizing and evaluating existing studies on distributed scheduling problems, we analyze the achievements and current research status in this field and discuss ongoing studies. Insights regarding prior works are discussed to uncover future research directions, particularly swarm intelligence and evolutionary algorithms, which are used for managing distributed scheduling problems in manufacturing systems. This work focuses on journal papers discovered using Google Scholar. After reviewing the papers, in this work, we discuss the research trends of distributed scheduling problems and point out some directions for future studies.

Key words: distributed manufacturing systems; distributed scheduling problems; modeling and optimization; intelligent optimization methods

1 Introduction

With economic globalization and rising customer demands, market competition has become increasingly fierce. Manufacturing enterprises must extend their production mode into distributed environments and establish multiple factories in various remote geographical locations. Currently, distributed manufacturing systems are extensively applied in various types of manufacturing industries, such as automotive[1], steel-making[2], and food and chemical processing[3]. The modeling and scheduling of distributed manufacturing systems have attracted considerable attention because of their significant effects on improving operational efficiency[4–7].

In industrial systems, scheduling plays an essential role in decreasing production cost and improving customer satisfaction[8–12]. In the past decades, a large number of studies on scheduling problems in manufacturing and service systems have been conducted. These problems can be classified as single-machine scheduling[13, 14], parallel-machine scheduling[15, 16], flow-shop scheduling[17–19], job-shop scheduling[20, 21], and their variants[22, 23]. In recent years, researchers have proposed a new scheduling method, i.e., distributed scheduling, which aims at scheduling distributed manufacturing systems[24]. Distributed scheduling

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Manuscript received: 2021-01-05; accepted: 2021-01-27

methods have wide applications in different areas, such as operating room scheduling[25–28], distributed computing systems[29], and geographically distributed configuration systems[30]. In the manufacturing domain, distributed scheduling focuses on simultaneously scheduling all factories in distributed manufacturing systems. Compared with the problems of scheduling a single factory, distributed scheduling problems have more highly complex characteristics, which are presented as follows:

(1) In contrast to traditional scheduling problems, where we just consider job allocation among machines and job sequence on machines at a factory, in distributed production scheduling problems, we must additionally determine job allocation/assignment among various factories.

(2) In practice, decision-makers usually consider time-related criteria, such as achieving maximum completion time (makespan), flow time, and tardiness minimization. However, we must also consider the workload balance among factories and total production cost in distributed manufacturing environments.

(3) Generally, factories have geographically remote locations, and thus it is not feasible to accurately determine information regarding their production circumstances, such as order arrival, machine breakdown, and delivery time change. Therefore, there are many uncertainties in the distributed production process, which increases the difficulty of scheduling them.

In recent years, distributed scheduling problems have attracted significant research interest. Many scholars have devoted efforts and attention to study the modeling and optimization of scheduling various distributed manufacturing systems. Meanwhile, some researchers have contributed to summarizing existing studies on distributed scheduling problems[31–34]. Toptal and Sabuncuoglu[31] provided a literature survey on distributed scheduling algorithms in a distributed architecture. They made an analysis of the difference between decentralized and centralized scheduling systems and gave a detailed definition of distributed scheduling systems. Behnamian and Ghomi[32] analyzed previous works on distributed scheduling on various models, such as distributed single machine, parallel machine, flow shop, and job shop. Chaouch et al.[33] focused on distributed job shop scheduling problems and summarized optimization approaches for solving them. Lohmer and Lasch[34] analyzed planning and scheduling problems in distributed manufacturing systems and summarized the literature in accordance with shop types, objective functions, and solution methods.

The abovementioned reviews aim at introducing the applications and advantages of distributed scheduling problems in different areas and analyzing the optimization approaches in solving distributed planning and scheduling problems. In contrast to the above literature, this work focuses on distributed manufacturing systems and analyzes recent studies on various models. In addition, it mainly focuses on analyzing the optimization approaches for distributed scheduling problems. Owing to the complexity of distributed scheduling problems, conventional mathematical optimization approaches are unable to solve them within an acceptable amount of time. Thus, we focus on approximation algorithms, particularly Swarm Intelligence (SI) and Evolutionary Algorithms (EAs), for handling distributed production scheduling problems, although these algorithms do not guarantee optimal solutions.

The essential components of a literature review are the scope and purpose. This paper focuses on summarizing and synthesizing distributed scheduling problems in manufacturing systems and their optimization approaches. The main objectives of this paper are as follows: (1) classification of distributed manufacturing systems; (2) evaluation of the model of distributed scheduling problems; (3) classification of optimization objectives, such as makespan, tardiness, energy consumption, and machine workload; (4) classification of optimization methods, particularly SI and EAs; and (5) determination of the research directions of distributed scheduling problems in manufacturing systems. According to the purpose and review contents of this work, we define the words "distributed manufacturing", "distributed production", "multi-factory production", "distributed/parallel scheduling", "distributed parallel-machine scheduling", "distributed flow-shop scheduling", "distributed job-shop scheduling", "distributed open-shop scheduling", "swarm intelligence", "evolutionary algorithms", "meta-heuristics", and their combinations as index keywords in Google Scholar. All the keywords are presented in Table 1. This work focuses on academic journals that publish high-quality papers. Accordingly, we collected the journal publications. By employing the keywords

Table 1 Keywords indexed in Google Scholar.

Problem-related keyword	Scheduling-related keyword	Optimization method-related keyword
Distributed manufacturing	Distributed/parallel scheduling	SI
Distributed factory	Multi-factory scheduling	EA
Distributed production	Distributed factory scheduling	Meta-heuristics
Multi-factory production	Distributed parallel machine/ flow shop/ job shop/ open shop scheduling	Genetic algorithm, particle swarm optimization, etc.

in Table 1 to search the literature related to the topic "distributed scheduling problems in manufacturing systems", we found 97 publications published from 2010 until January 2021, and the corresponding journals are listed in Table 2. 85% of the acquired papers were published in 16 journals, where at least two papers have been published. Seventeen papers were published in the journal *International Journal of Production Research*, which was ranked first among all the journals considering the number of papers published in the dataset. In addition, the journal *Swarm and Evolutionary Computation* was ranked second with ten papers.

Table 2 Reviewed journals and number of relevant papers.

Journal's name	Number
International Journal of Production Research	17
Swarm and Evolutionary Computation	10
Computers & Industrial Engineering	8
Expert Systems with Applications	8
Computers & Operations Research	6
Applied Soft Computing	5
IEEE Access	5
Knowledge-Based Systems	4
Engineering Optimization	3
Journal of Intelligent Manufacturing	3
Engineering Applications of Artificial Intelligence	2
European Journal of Operational Research	2
IEEE Transactions on Cybernetics	2
IEEE Transactions on Systems, Man, and Cybernetics: Systems	2
International Journal of Production Economics	2
Mathematical Problems in Engineering	2
Applied Sciences	1
Enterprise Information Systems	1
IEEE Transactions on Electrical & Electronic Engineering	1
IEEE Transactions on Automation Science and Engineering	1
IEEE Transactions on Emerging Topics in Computational Intelligence	1
IEEE Transactions on Industrial Informatics	1
International Journal of Computational Intelligence Systems	1
Journal of Cleaner Production	1
Journal of the Operations Research Society of China	1
Memetic Computing	1
Omega	1
Procedia Computer Science	1
Procedia CIRP	1
Production Engineering	1
Simulation Modelling Practice and Theory	1
The International Journal of Advanced Manufacturing Technology	1

2 Problem

Generally, distributed production scheduling problems are considered and modeled about classical shop scheduling problems. Table 3 reports the literature about distributed production scheduling and shows 97 publications that are recorded from 2010 to 2021. The types of production shops include (hybrid) flow shop, parallel-machine scheduling, (flexible) job shop, and generally distributed production environments. In some studies, the distributed scheduling problems are integrated with other problems, e.g., distribution problems[35–37], planning problems[38, 39], resource allocation problems[39], and vehicle routing problems[40]. Few publications focus on real-life areas, e.g., semiconductor wafer manufacturing[41].

Real-life constraints or special phases in various shop types are considered in many problems on distributed production scheduling. Flow time-related constraints, including fuzzy processing time, stochastic processing time, setup time, and transportation time, are considered in Refs. [42–52]. Production shop-related constraints, including no wait, no idle, blocking, limited buffer, and lot streaming, are addressed in Refs. [40, 47, 52–63]. In distributed production scheduling, a one- or two-stage assembly line as a special phase in flow shops and job shops have been researched in many publications[42, 45, 51, 64–72]. Some other constraints are also considered in distributed production scheduling, e.g., job re-entrant[73], unrelated machines[74], and heterogeneous production shops[48, 75].

Modeling distributed production scheduling problems is a way of employing various methods to solve them. Modeling methods involve solution approaches

Table 3 Literature about distributed production scheduling.

Ref.	Author and year	Shop type	Constraint	Model type	Objective	Method
35	Chang et al., 2014	Integrated production and distribution		Mixed Integer Linear Programming (MILP)	Delivery time, distribution cost	SI/EA
36	Gharaei and Jolai, 2018	Integrated scheduling and distribution		Mixed Linear Programming (MIP)	Tardiness, distribution cost	SH/DR, SI/EA
37	Marandi an Fatemi, 2019	Production and distribution scheduling		MIP	Makespan	SI/EA, CPLEX
38	Mishra et al., 2012	Planning	Supply chain environment	General mathematical model	Cost, machining time	SI/EA
39	Zhang et al., 2017	Integration planning and scheduling		General mathematical model	Makespan	SI/EA
40	Ribas et al., 2017	Flowshop	Blocking	General mathematical model	Makespan	SI/EA
41	Dong and Ye, 2019	Semiconductor wafer manufacturing		MIP	Makespan, carbon emissions, tardiness	SH/DR, SI/EA
42	Xiong et al., 2014	Flowshop	Two-stage assembly line, setup time	General mathematical model	Total flow time	SI/EA
43	Behnamian, 2014	General manufacturing environment	Transportation time	MILP	Cost and profit	CPLEX, SI/EA
44	Zhang et al., 2016	Job shop	Fuzzy processing time	General mathematical model	Makespan	SI/EA
45	Neira et al., 2017	Flowshop	Assembly line, stochastic processing time	None	Makespan	Others
46	Fu et al., 2019	Distributed manufacturing system	Stochastic	MIP	Total tardiness, energy consumption	SI/EA
47	Shao et al., 2019	Flowshop	Blocking	General mathematical model	Makespan	SI/EA
48	Li et al., 2020	Hybrid flowshop	Heterogeneous, setup time	MILP	Makespan	SI/EA
49	Ying et al., 2020	Flowshop	Flexible assembly, sequence-independent setup time	MILP	Makespan	SI/EA
50	Zheng et al., 2020	Flowshop	Fuzzy processing time	General mathematical model	Fuzzy tardiness and robustness	SH/DR, SI/EA
51	Song and Lin, 2020	Flowshop	Assembly, setup time	MILP	Makespan	SI/EA
52	Li et al., 2021	Flowshop	No-wait	General mathematical model	Makespan	SI/EA
53	Komaki and Malakooti, 2017	Flowshop	No-wait	General mathematical model	Makespan	SI/EA
54	Ying et al., 2017	Flowshop	No-idle	MIP	Makespan	SI/EA
55	Ying and Lin, 2017	Flowshop	Blocking	MIP	Makespan	SI/EA
56	Shao et al., 2017	Flowshop	No-wait	General mathematical model	Makespan	SH/DR, SI/EA
57	Cheng et al., 2019	Flowshop	No-idle	MILP	Makespan	SI/EA
58	Zhang et al., 2018	Flowshop	Blocking	General mathematical model	Makespan	SH/DR, SI/EA
59	Ribas et al., 2019	Flowshop	Blocking	None	Total tardiness	SI/EA
60	Chen et al., 2019	Flowshop	No-idle	General mathematical model	Makespan, total energy consumption	SI/EA
61	Zhao et al., 2020	Flowshop	Blocking	General mathematical model	Makespan	SI/EA

(To be continued)

Table 3 Literature about distributed production scheduling.

(Continued)

Ref.	Author and year	Shop type	Constraint	Model type	Objective	Method
62	Zhao et al., 2020	Flowshop	No-idle	None	Assembly, completion time	SI/EA
63	Shao et al., 2020	Flowshop	Blocking	MILP	Makespan	SI/EA
64	Hatami et al., 2013	Flowshop	Assembly line	MILP	Makespan	SH/DR, SI/EA
65	S. Y. Wang and L. Wang, 2015	Flowshop	Assembly line	General mathematical model	Makespan	SI/EA
66	Deng et al., 2016	Flowshop	Two-stage assembly line	MILP	Makespan	SI/EA
67	Lin and Zhang, 2016	Flowshop	Assembly line	General mathematical model	Makespan	SI/EA
68	Lin et al., 2017	Flowshop	Assembly line	General mathematical model	Makespan	SH/DR, SI/EA
69	Zhang and Xing, 2018	Flowshop	Two-stage assembly line	General mathematical model	Total flow time	SI/EA
70	Wu et al., 2019	Flexible Job Shop Scheduling (FJSP)	Assembly line	General mathematical model	Earliness/tardiness, total cost	SI/EA
71	Zhang et al., 2020	Flowshop	Flexible assembly line	MILP	Makespan	SI/EA
72	Lei et al., 2020	Flowshop	Two-stage assembly flow shop	General mathematical model	Makespan	SI/EA
73	Rifai et al., 2016	Flowshop	Reentrant	General mathematical model	Makespan, cost, and tardiness	SI/EA
74	Lei et al., 2020	Parallel machine scheduling	Unrelated parallel machines	General mathematical model	Makespan	SI/EA
75	Meng and Pan, 2020	Flowshop	Heterogeneous, lot-streaming, setup time	MILP	Makespan	SH/DR, SI/EA
76	Naderi and Ruiz, 2010	Flowshop		MILP	Makespan	SH/DR
77	Azab and Naden, 2014	Job shop		MILP	Makespan	SH/DR, CPLEX
78	Naderi and Azab, 2015	Job shop		MILP	Makespan	SI/EA
79	Behnamian and Ghomi, 2015	General manufacuring environment		MILP	Total completion time	SH/DR, CPLEX
80	Ying and Lin, 2018	Flowshop	Multiprocessor tasks	MILP	Makespan	SI/EA
81	Shao et al., 2019	Flowshop	No-wait, setup time	MILP	Makespan, total weight tardiness	SH/DR, SI/EA
82	Pan et al., 2019	Flowshop		MIP	Makespan	SI/EA
83	Huang et al., 2020	Flowshop	Sequence-dependent setup time	MILP	Makespan	SI/EA
84	Meng et al., 2020	FJSP		MILP, constraint programming	Makespan	CPLEX
85	Gong et al., 2020	General manufacturing environment		MILP	Makespan, total energy consumption	SH/DR, SI/EA
86	Lu et al., 2020	Flowshop		MILP	Makespan, total energy consumption	SI/EA
87	Wang et al., 2020	Flowshop		MILP	Makespan, energy consumption	SI/EA
88	Pan et al., 2020	Flowshop	Group scheduling	MILP	Makespan	SI/EA

(To be continued)

Table 3 Literature about distributed production scheduling.

(Continued)

Ref.	Author and year	Shop type	Constraint	Model type	Objective	Method
89	Xiong et al., 2020	Flowshop	Concrete precast	MINLP, MILP	Total weighted earliness and tardiness	SI/EA
90	J. Wang and L. Wang, 2018	Flowshop		General mathematical model	Makespan, total energy consumption	SH/DR, SI/EA
91	Fu et al., 2019	Flowshop	Total tardiness threthold	Chance-constrained programming	Makespan, energy consumption	SI/EA
92	Luo et al., 2020	FJSP	Transfer	General mathematical model	Makespan, workload, energy consumption	SI/EA
93	Jiang et al., 2020	FJSP		General mathematical model	Makespan, energy consumption	SI/EA
94	Guo et al., 2015	General manufacturing environment	Production monitoring	Intelligent decision support system	Tracking and monitoring	Others
95	Zou et al., 2018	Integrated scheduling and vehicle routing		General mathematical model	Maximum route time	SH/DR, SI/EA
96	Zhang and Gen, 2010	Distributed manufacturing system		General mathematical model	Total processing time, workload	SI/EA
97	Giovanni and Pezzella, 2010	FJSP		General mathematical model	Makespan	SI/EA
98	Gao and Chen, 2011	Flowshop		General mathematical model	Makespan	SH/DR, SI/EA
99	Liu et al., 2014	FJSP	Fastener manufacturer	General mathematical model	Makespan	SI/EA
100	Chang and Liu, 2017	FJSP		General mathematical model	Makespan	SI/EA
101	Wu et al., 2017	FJSP			None	SI/EA
102	Viagas et al., 2018	Flowshop		General mathematical model	Total flow time	SH/DR, SI/EA, lower bounds
103	Lu et al., 2018	FJSP		General mathematical model	Makespan	SI/EA
104	Cai et al., 2018	Flowshop	Transportation and eligibility	General mathematical model	Makespan, lateness, cost	SH/DR, SI/EA
105	Wang et al., 2013	Flowshop		General mathematical model	Makespan	SH/DR, SI/EA
106	Xu et al., 2014	Flowshop		General mathematical model	Makespan	
107	Zhang et al., 2018	Flowshop		General mathematical model	Makespan	SI/EA
108	Meng et al., 2019	Flowshop		General mathematical model	Makespan	SI/EA
109	Yang and Xu, 2020	Flowshop	Flexible assembly and batch delivery	General mathematical model	Total cost, tardiness	SI/EA
110	Gao et al., 2013	Flowshop		General mathematical model	Makespan	SI/EA
111	Li et al., 2018	FJSP		General mathematical model	Makespan, maximal workload, and earliness/tardiness	SH/DR, SI/EA
112	Chaouch et al., 2017	Job shop		Disjunctive graph	Makespan	SI/EA
113	Zhang and Xing, 2019	Flowshop	Limited-buffer	General mathematical model	Makespan	SH/DR, SI/EA

(To be continued)

Table 3 Literature about distributed production scheduling.

(Continued)

Ref.	Author and year	Shop type	Constraint	Model type	Objective	Method
114	Naderi and Ruiz, 2014	Flowshop		General mathematical model	Makespan	SI/EA
115	Pan et al., 2019	Flowshop		General mathematical model	Total flow time	SH/DR, SI/EA
116	Lin et al., 2013	Flowshop		General mathematical model	Makespan	SH/DR, SI/EA
117	Viagas and Framinan, 2015	Flowshop		General mathematical model	Makespan	
118	Ruiz et al., 2019	Flowshop		General mathematical model	Makespan	SH/DR, SI/EA
119	Shao et al., 2020	Hybrid flowshop		General mathematical model	Makespan	SH/DR, SI/EA
120	Mao et al., 2020	Flowshop	Preventive maintenance	General mathematical model	Makespan	SI/EA
121	Deng and Wang, 2017	Flowshop		General mathematical model	Makespan, total tardiness	SI/EA
122	J. Wang and L. Wang, 2020	Flowshop		General mathematical model	Makespan	SI/EA
123	Bargaoui et al., 2017	Flowshop		None	Makespan	SI/EA
124	Zhang et al., 2017	Distributed manufacturing resource allocation		General mathematical model	Operating time, cost, risk, and quality	SI/EA
125	Hao et al., 2019	Hybrid flowshop		General mathematical model	Makespan	SI/EA
126	Li et al., 2019	Flowshop	Parallel batching, deteriorating jobs	General mathematical model	Makespan	SH/DR, SI/EA
127	Li et al., 2019	Flowshop	Distance coefficient	General mathematical model	Makespan	SH/DR, SI/EA
128	Huang et al., 2020	Flowshop	Sequence-dependent setup time	General mathematical model	Makespan	SI/EA
129	Lei and Wang, 2019	Hybrid flowshop	Two-stage flow shop	General mathematical model	Makespan	SI/EA
130	Cai et al., 2020	Hybrid flowshop		General mathematical model	Makespan, total tardiness	SI/EA
131	Sang et al., 2019	Flowshop		General mathematical model	Total flow time	SI/EA

and algorithms. Mathematical programming is usually used for modeling distributed production scheduling problems, especially for exact methods[35–37, 41, 43, 46, 48, 49, 51, 54, 55, 57, 63, 64, 66, 71, 75–89]. General mathematical models can be used for Simple Heuristics (SHs), Dispatch Rules (DRs), SI, and EAs to calculate objectives. For scheduling objectives, the completion time-related and machine workload-related ones are the most evaluated. Energy consumption and low-carbon-related objectives are attracting increasing attention; they can be considered as one of multiple objectives and simultaneously optimized with traditional objectives[46, 60, 85–87, 90–93].

For distributed production scheduling problems, few researchers have used real-life cases[38, 41, 94, 95]. Most instances are extended from the benchmark of classical flow-shop and job-shop scheduling problems. The methods for solving distributed production scheduling problems include exact methods, SHs or DRs, SI, and EAs. For SI and EAs, various strategies are used to improve their local and global searching performance. The corresponding contents will be discussed and analyzed in the next section.

3 Method

Distributed scheduling problems in manufacturing systems are more complicated than traditional scheduling problems because we must first decide job assignments among factories and then make decisions on their allocation and sequence on machines. Distributed scheduling problems have been proven to be NP-hard[76]. Hence, the existing studies devote much effort to solve them by employing heuristic methods, exact approaches, SI, and EAs. Table 4 presents the employed optimization approaches in the relevant literature. Figure 1 shows the percentage of optimization approaches used for solving distributed scheduling problems. The findings show that most of the prior studies have chosen SI and EAs for coping with distributed scheduling problems. A detailed analysis is given in the following subsection.

Table 4 Optimization approaches in the relevant literature.

Ref.	Author and year	Optimization approach			
		Heuristic	Exact	Swarm intelligence or evolutionary algorithm	Improving strategy
35	Chang et al., 2014			Ant Colony Optimization (ACO)	
36	Gharaei and Jolai, 2018			Multi-agent approach, Bees algorithm based on decomposition	Local search
37	Marandi and Fatemi, 2019		CPLEX	Imperialist Competitive Algorithm (ICA)	Local search based on Simulated Annealing (SA)
38	Mishra et al., 2012			Genetic Algorithm (GA) and SA	
39	Zhang et al., 2017			ICA and GA	
40	Ribas et al., 2017			Iterative Local Search (ILS) and Variable Neighborhood Search (VNS)	Solution initialization with constructive heuristics
41	Dong and Ye, 2019			Grey Wolf Optimization (GWO)	Population initialization with learning strategy
42	Xiong et al., 2014			GA, Differential Evolution (DE), VNS	
43	Behnamian, 2014		CPLEX	Tabu Search algorithm (TS) and VNS	Local search
44	Zhang et al., 2016			GA	Local enhancement strategy
45	Neira et al., 2017			Randomized adaptive search procedure with simulation approach	
46	Fu et al., 2019			Brain Storm Optimization (BSO)	Clustering method
47	Shao et al., 2019			Fruit Fly Optimization (FFO)	Population initialization with heuristic, local search
48	Li et al., 2020			Artificial Bee Colony algorithm (ABC)	
49	Ying et al., 2020	TP_DNEH		Iterated Greedy Algorithm (IGA)	Local search
50	Zheng et al., 2020	mNEH2		Estimation of Distribution Algorithm (EDA) and IGA	Local search
51	Song and Lin, 2020			Genetic Programming (GP)+SA	
52	Li et al., 2020			Discrete ABC	Heuristics, VND
53	Komaki and Malakooti, 2017			VNS	Local search
54	Ying et al., 2017			Iterative reference greedy algorithm	Solution initialization with heuristics
55	Ying and Lin, 2017			IGA and TS	Search with tabu list and cooling process
56	Shao et al., 2017			IGA	Solution initialization with heuristics, speed-up strategy
57	Cheng et al., 2019			Cloud theory-based IGA	Local search
58	Zhang et al., 2018	SPT, LPT, large-small method, NEH		Discrete DE	Population initialization with heuristic method, local search

(To be continued)

Table 4 Optimization approaches in the relevant literature.

(Continued)

Ref.	Author and year	Optimization approach			
		Heuristic	Exact	Swarm intelligence or evolutionary algorithm	Improving strategy
59	Ribas et al., 2019			IGA	
60	Chen et al., 2019			Collaborative Optimization Algorithm (COA)	Population initialization with heuristic
61	Zhao et al., 2020			Discrete DE (DDE)	Population initialization with heuristic methods
62	Zhao et al., 2020			Water Wave Optimization (WWO)	Heuristics, local search, VNS
63	Shao et al., 2020	Heuristics based on NEH		IGA	Local search
64	Hatami et al., 2013	Constructive heuristics		Variable Neighborhood Decent (VND)	
65	S. Y. Wang and L. Wang, 2015			EDA and Memetic Algorithm (MA)	Local search
66	Deng et al., 2016			Competitive MA (CMA)	Ring-based neighbor-structure, knowledge-based local search
67	Lin and Zhang, 2016			Biogeography-Based Optimization (BBO)	Local search
68	Lin et al., 2017	Low-level heuristics		Backtracking Search (BS)	Hyper-heuristic approach
69	Zhang and Xing, 2018			Social Spider Optimization (SSO)	Problem-specific local search, restart strategy
70	Wu et al., 2019			DE and SA	Local search
71	Zhang et al., 2020			SSO	Local search based on meta-Lamarckian learning
72	Lei et al., 2020			Teaching-Learning-Based Optimization (TLBO)	
73	Rifai et al., 2016			Adaptive Large Neighborhood Search (ALNS)	
74	Lei et al., 2020			ICA	Memory and neighborhood structures-based improving strategy
75	Meng and Pan, 2020	Constructive heuristics		ABC	Collaboration mechanism, restart strategy
76	Naderi and Ruiz, 2010	Heuristics based on dispatching rules		VND	
77	Azab and Naderi, 2014	Greedy heuristics	CPLEX		
78	Naderi and Azab, 2015			SA	Local search, restart operation
79	Behnamian and Ghomi, 2015		CPLEX	Monte Carlo algorithm	Solution initialization with heuristics, local search
80	Ying and Lin, 2018			Self-tuning IGA	Solution initialization with heuristics
81	Shao et al., 2019			Pareto-based EDA	Population initialization with heuristic method, local search
82	Pan et al., 2019	Constructive heuristics		VNS and IGA	
83	Huang et al., 2020			IGA	Restart scheme (IGR), control parameter, local search

(To be continued)

Table 4 Optimization approaches in the relevant literature.

(Continued)

Ref.	Author and year	Optimization approach			
		Heuristic	Exact	Swarm intelligence or evolutionary algorithm	Improving strategy
84	Meng et al., 2020		CPLEX		
85	Gong et al., 2020			MA	Balance-transfer method, local search
86	Lu et al., 2020			Iterative Greedy (IG)	Local search
87	Wang et al., 2020			Whale Swarm Algorithm (WSA)	Problem-dependent local search
88	Pan et al., 2020			EA	Heuristics, reinitialization scheme
89	Xiong et al., 2020	NEH		IGA and TS	Local search
90	J. Wang and L. Wang, 2018	NEH		Knowledge-based Cooperative Algorithm (KCA)	Population initialization with heuristic method, local search
91	Fu et al., 2019			BSO	Clustering approach
92	Luo et al., 2020			MA	Three effective neighborhood structures
93	Jiang et al., 2020			MOEA with decomposition	
94	Guo et al., 2015			Multi-objective EA	
95	Zou et al., 2018	Backward and forward batching method		GA and two-stage algorithm	Local search
96	Zhang and Gen, 2010			GA	
97	Giovanni and Pezzella, 2010			GA	Local search
98	Gao and Chen, 2011	NEH2		GA and VND	Local search
99	Liu et al., 2014			GA	Probability-based encoding operator
100	Chang and Liu, 2017			GA	
101	Wu et al., 2017			GA	
102	Viagas et al., 2018	Constructive heuristics		GA	Population initialization with heuristic methods, local search
103	Lu et al., 2018			GA	
104	Cai et al., 2018	NEH adaptive (NEHA)		Nondominated Sorting Genetic Algorithm II (NSGA-II)	Population initialization with heuristic method, local search
105	Wang et al., 2013	Heuristics with SPT, LPT, and NEH		EDA	Population initialization with heuristics, local search
106	Xu et al., 2014			Immune Algorithm (IA)	Problem-feature-based local search
107	Zhang et al., 2018			VNS and Particle Swarm Optimization (PSO)	Population initialization with heuristic method

(To be continued)

Table 4 Optimization approaches in the relevant literature.

(Continued)

Ref.	Author and year	Optimization approach: Heuristic	Exact	Swarm intelligence or evolutionary algorithm	Improving strategy
108	Meng et al., 2019			VND, ABC, and IGA	Solution initialization with heuristic rules
109	Yang and Xu, 2020	Batch allocation strategy		VND and IGA	
110	Gao et al., 2013			TS	Local search
111	Li et al., 2018			Pareto-based TS	Solution initialization with heuristic approaches
112	Chaouch et al., 2017			ACO	Neighborhood strategy
113	Zhang and Xing, 2019	Constructive heuristics		DE	Population initialization with heuristic approach
114	Naderi and Ruiz, 2014			Scatter Search (SS)	Subset generation combination methods, local search
115	Pan et al., 2019	Constructive heuristics		ABC, SS and IGA	Solution initialization with heuristics, reference local search
116	Lin et al., 2013	NEH2		IGA	
117	Viagas and Framinan, 2015	NEH2		Bounded-search IGA	Local search
118	Ruiz et al., 2019	NEH2_en based on NEH		IGA	Solution initialization based on a new NEH2_en, local search
119	Shao et al., 2020	Distributed NEH (DNEH)		IGA	Multi-search construction with greedy insertion
120	Mao et al., 2020	INEH2_dp		Multi-start IGA	Heuristics, local search
121	Deng and Wang, 2017			CMA	Local search
122	J. Wang and L. Wang, 2020			MA	
123	Bargaoui et al., 2017			Chemical Reaction Optimization (CRO)	NEH, One-Point crossover and greedy strategy
124	Zhang et al., 2017			TLBO	
125	Hao et al., 2019			BSO	Improved NEH, improved crossover operator
126	Li et al., 2019	Batch assignment, right-shifting heuristics		ABC	Local search
127	Li et al., 2019			ABC	Distributed Iterated Greedy (DIG)
128	Huang et al., 2020	Constructive heuristics		Discrete ABC	Local search
129	Lei and Wang, 2019			Shuffled Frog-Leaping Algorithm (SFLA)	Population initialization with heuristic, memeplex grouping
130	Cai et al., 2020			SFLA	
131	Sang et al., 2019			Invasive Weed Optimization (IWO)	Local search

3.1 SI and EAs

To address the highly complicated distributed scheduling problems, SI and EAs have been adopted, including GA[38, 39, 44, 51, 88, 93–104], EDA[50, 81, 105], MA[106], VNS[40, 42, 43, 53, 64, 76, 82, 98, 107–109], TS[43, 55, 89, 110, 111], PSO[107], ACO[35, 112], DE[42, 58, 61, 70, 113], SS[114, 115], IGA[49, 50, 55–57, 59, 63, 80, 82, 83, 86, 89, 108, 109, 115–120], SA[38, 51, 70, 78], MA[65, 66, 85, 92, 121, 122], BBO[67], ICA[37, 39, 74], CRO[123], COA[60], FFO[47], TLBO[124], SSO[69, 71], KCA[90], GWO[41], BSO[46, 91, 125], SFLA[129, 130], ABC[48, 52, 75, 108, 115, 126–128], IWO[131], WSA[87], WWO[62]. As shown in Fig. 1, SI and EAs account for 74% of all the employed methods. Thus, SI and EAs are the mainstream methods for addressing distributed scheduling problems. Generally, they do not depend on problem characteristics and have no requirements for mathematical models. The procedure of SI and EAs is given below:

Step 1: Initialize the algorithm parameters and generate a set of solutions as a population.

Step 2: Calculate the objective function values of solutions in the population.

Step 3: Generate new solutions by adopting the solutions in the population.

Step 4: Evaluate newly generated solutions and update the population.

Step 5: If a given termination is reached, go to Step 6; otherwise, go to Step 3.

Step 6: Output the best-acquired solution and the corresponding objective function value.

SI and EAs have strong stochasticity. To enhance their search performance, many studies have adopted improvement strategies. These studies account for 71% of all the articles, as shown in Fig. 2. SI and EAs attach importance to enhance the exploration ability for quickly

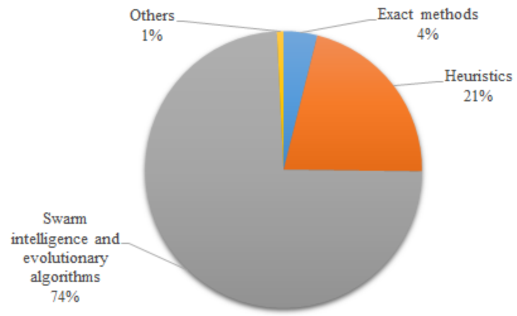

Fig. 1 Optimization approaches for solving distributed scheduling problems.

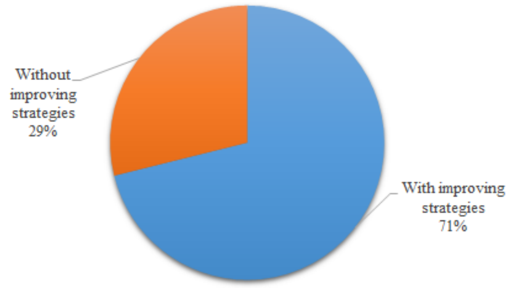

Fig. 2 SI and EAs with and without improvement strategies.

finding promising regions in the solution space, while they are not good enough to perform the exploitation ability in the found promising regions. As shown in the above procedure, they usually start with a population. Normally, their search performance greatly benefits from a high-quality population. Hence, some studies generate a set of solutions with heuristics to construct a better initial population. In addition, most studies have used local search methods to enhance their exploitation ability. Accordingly, balancing the exploration and exploitation abilities has been regarded as a challenging work in designing SI and EAs.

3.2 Other approaches

As shown in Fig. 1, some studies have selected heuristics and exact approaches to solve distributed production scheduling problems. The studies employing heuristics account for 21% of the total, and those adopting exact methods account for 4% of the total. Heuristics can acquire feasible solutions for distributed scheduling problems with less computation resources by applying dominated properties. They have the clear characteristics of quickly finding solutions regardless of the quality of solutions. Conversely, exact methods aim at attaining optimal solutions without consideration of computation resources. Thus, most of the existing studies have used them to solve small-scale problems, considering that they have the capacity to reach globally optimal solutions within reasonable running time. To make a trade-off between the solution quality and computation resources, the previous works have widely employed SI and EAs, combining heuristics and exact methods, to solve distributed scheduling problems.

4 Research Status and Trend

Distributed scheduling problems in manufacturing systems have become an important research focus over the last few years. As shown in Fig. 3, the number of publications for solving distributed scheduling problems in manufacturing areas rapidly increased. Particularly, in the most recent three years, it has grown rapidly and has reached a maximum in 2019 with 21 articles. The results show that distributed production scheduling problems have recently attracted much attention, and studying their modeling and optimization are very important to effectively organize and manage distributed manufacturing systems.

4.1 Single objective vs. multiple objectives

Production scheduling problems involve many criteria, such as minimizing the makespan, flow time, tardiness, and energy consumption. As shown in Fig. 4, most of the previous studies considered optimizing only one objective function when solving distributed scheduling problems in manufacturing systems. Much attention has been given to multi-objective optimization in recent years, especially in 2019 and 2020, where nearly half of the publications focused on multi-objective distributed scheduling problems. Generally, decision-makers have

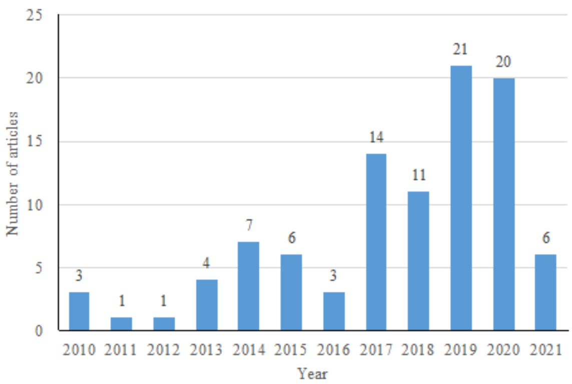

Fig. 3 Year-wise publication count of distributed scheduling problems.

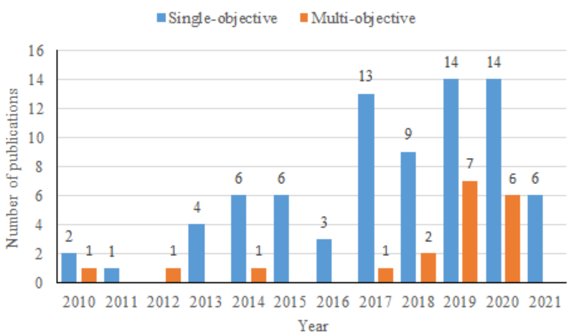

Fig. 4 Year-wise comparisons of single-objective and multi-objective publications

to consider multiple criteria to determine a trade-off among them when making scheduling decisions. In such a situation, multi-objective optimization needs to be employed for handling distributed scheduling problems in manufacturing systems.

4.2 Objective functions

The publication count of various objective functions shown in Fig. 5 proves that most of the existing studies, accounting for 67% among all the publications, considered minimizing the makespan, which is a frequently used objective to maximize machine utilization in real-world manufacturing systems. In addition, minimizing tardiness, which accounts for 10%, has received much interest due to their great influence on customer satisfaction. The prior works also focused on decreasing the energy consumption in scheduling the distributed manufacturing systems because of the huge pressure from the government and public on environmental protection issues. Particularly, the workload balance among factories is an important criterion for distributed manufacturing systems, and 3% of the existing studies considered the workload-related objectives.

4.3 SI and EAs

To further analyze the applications of diverse SI and EAs, we classify the publications regarding them for handling distributed production scheduling problems. The number of articles that used the various methods is illustrated in Fig. 6. A total of 27 algorithms were adopted for solving distributed scheduling problems. The IGA, which addresses single- and multi-objective distributed scheduling problems, is the most popular among all the adopted methods, with a total of 20 publications. The second most popular method is GA, which has 17 publications. For "Others", some search approaches

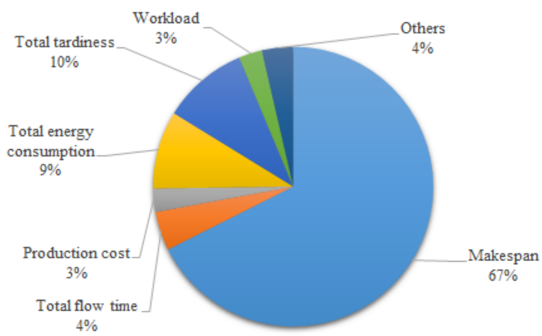

Fig. 5 Publication count of various objective functions.

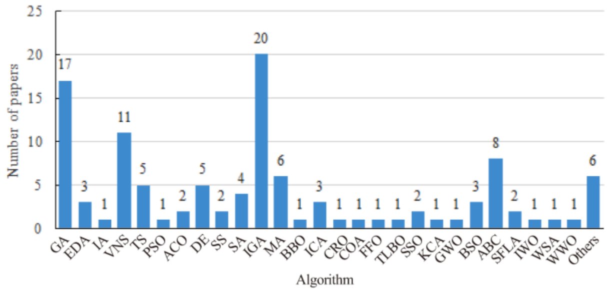

Fig. 6 Publication count of specific SI and EAs.

based on neighborhood structures[73], simulation[45], and multi-agent methods[36] were employed. The above analysis clearly shows that SI and EAs have been employed to handle distributed scheduling problems, which further confirms their excellent performance in solving this kind of problem.

5 Conclusion and Further Direction

This work provides an overall picture of the advanced research on distributed scheduling problems in manufacturing systems. After starting with an introduction to distributed scheduling problems, we discussed their classification and analyzed them. Next, we analyzed the framework of optimization approaches on distributed scheduling problems, particularly SI and EAs. Finally, we identified the research trends according to the articles based on the publication count of the publication year, single- and multi-objective optimizations, objective functions, and various SI and EAs.

Analyzing the research achievements and the status of distributed scheduling problems in manufacturing systems, we explored future research directions:

(1) Optimizing highly important objectives

According to the above summary, the time-related and cost-effective criteria have been taken into account in solving distributed scheduling problems. With fierce market competition and economic globalization, the government and public have put forward new requirements for industrial development, such as energy reduction and quality improvement. Nowadays, decision-makers attach great importance to energy conservation operations in industrial systems[132]. A significant topic is energy-efficient scheduling that aims at decreasing the total energy consumption of manufacturing systems. Therefore, highly important objectives, such as decreasing energy consumption[133–135] and improving processing quality[136], need to be considered in solving distributed production scheduling problems.

(2) Modeling with consideration of uncertainties

Generally, there are many uncertainties in industrial systems, such as order arrival and machine breakdown, which results in the production process being performed differently from what is planned[137–143]. According to the analysis, almost all of the existing studies focus on distributed scheduling problems in deterministic environments. Therefore, we should fully consider the uncertainties when making decisions for distributed scheduling problems. Generally, stochastic, fuzzy, and robust models can be formulated to mathematically describe distributed scheduling problems in uncertain environments. Furthermore, it is significant to explore the solution algorithms for these models by employing popular approaches and simulation optimization methods.

(3) Scheduling distributed manufacturing systems with heterogeneous factories

Nowadays, many scheduling systems, including distributed production scheduling, are heterogeneous because of the extensive applications of multi-purpose intelligent equipment in manufacturing systems[144]. As a result, jobs have various production routes in different factories. Scheduling heterogeneous factories are more complicated than scheduling homogeneous factories in distributed environments because the manufacturing process of jobs among factories has diverse production cost, processing quality, and energy consumption. Considering the significant applications of manufacturing systems with heterogeneous factories, it is necessary to perform modeling and optimization to effectively schedule them.

(4) Studying more distributed scheduling models and their applications

By analyzing the existing studies, we found that distributed scheduling models with parallel machines, flow shop, and job shop have received much attention due to their important applications in manufacturing systems. However, only a few studies are concerned with distributed open-shop scheduling problems, although they have essential applications in different areas, such as healthcare and vehicle inspection systems[145]. In addition, some distributed manufacturing systems with special circumstances, such as no wait, blocking, and lot streaming, should be fully taken into consideration because of their significance in the production environment where machines and jobs have specific requirements[146]. Distributed scheduling models can also be used to solve networking scheduling and control problems[147].

(5) Designing SI and EAs

Over the past years, SI and EAs have been successfully used to handle various complex optimization problems[148–152]. According to the analysis and discussion, they have excellent performance in addressing distributed scheduling problems in manufacturing systems, particularly those with complicated constraints and large solution spaces. Designing more highly efficient methods based on them, especially multiobjective optimization approaches for coping with multiobjective distributed scheduling problems, is an essential and promising direction. In addition, some local search methods based on dominated properties have shown better ability to enhance the performance of SI and EAs, and thus the design of problem-dependent local search strategies should be given enough consideration in future works.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China (Nos. 61603169, 61703220, and 61873328), China Postdoctoral Science Foundation Funded Project (No. 2019T120569), Shandong Province Outstanding Youth Innovation Team Project of Colleges and Universities of China (No. 2020RWG011), Shandong Province Colleges and Universities Youth Innovation Talent Introduction and Education Program, the Faculty Research Grants (FRG) from Macau University of Science and Technology, and Shandong Provincial Key Laboratory for Novel Distributed Computer Software Technology.

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