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
methods have wide applications in different areas, such as operating room scheduling\cite{25–28}, distributed computing systems\cite{29}, and geographically distributed configuration systems\cite{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\cite{31–34}. Toptal and Sabuncuoglu\cite{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\cite{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.\cite{33} focused on distributed job shop scheduling problems and summarized optimization approaches for solving them.

Lohmer and Lasch\cite{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
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.

## 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\[^{38, 75}\].

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

| Problem-related keyword                  | Scheduling-related keyword                  | Optimization method-related keyword | Journal’s name                                               | Number |
|------------------------------------------|--------------------------------------------|------------------------------------|-------------------------------------------------------------|--------|
| Distributed manufacturing                | Distributed/parallel scheduling            | SI                                 | *International Journal of Production Research*              | 17     |
| Distributed factory                      | Multi-factory scheduling                   | EA                                 | *Swarm and Evolutionary Computation*                        | 10     |
| Distributed production                   | Distributed factory scheduling             | Meta-heuristics                    | *Computers & Industrial Engineering*                        | 8      |
| Multi-factory production                 | Distributed parallel machine/flow shop/job shop/open shop scheduling | Genetic algorithm, particle swarm optimization, etc. | *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    |

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| 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 |
| 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 | Two-stage assembly line, setup time | MIP | Makespan, carbon emissions, tardiness | SH/DR, SI/EA |
| 42   | Xiong et al., 2014 | Flowshop | Transportation time | General mathematical model | Total flow time | SI/EA |
| 43   | Behnamian, 2014 | General manufacturing environment | Job shop | MILP | Cost and profit | CPLEX, SI/EA |
| 44   | Zhang et al., 2016 | Flowshop | 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.

| 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 Reentrant | General mathematical model | Makespan, cost, and tardiness | SI/EA  |
| 73   | Rifai et al., 2016 | Flowshop  | Unrelated parallel machines | General mathematical model | Makespan  | SI/EA  |
| 74   | Lei et al., 2020 | Parallel machine scheduling | Heterogeneous, lot-streaming, setup time | MILP       | Makespan  | SH/DR, SI/EA |
| 75   | Meng and Pan, 2020 | Flowshop  |            | MILP       | Makespan  | SH/DR  |
| 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 Gholami, 2015 | General manufacturing 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 | SI/EA  |
| 82   | Pan et al., 2019 | Flowshop  |            | MILP       | 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 | Total tardiness threshold | General mathematical model | Makespan, total energy consumption | SH/DR, SI/EA |
| 91   | Fu et al., 2019 | Flowshop | Transfer | Chance-constrained programming | Makespan, energy consumption | SI/EA |
| 92   | Luo et al., 2020 | FJSP | Concrete precast | General mathematical model | Makespan, workload, energy consumption | SI/EA |
| 93   | Jiang et al., 2020 | FJSP | Concrete precast | 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 | General mathematical model | 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 | SI/EA |
| 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                        | SH/DR, 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                        | SH/DR, SI/EA            |            |
| 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  | Bargayou et al., 2017    | Flowshop                   | None                            | General mathematical model      | 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\(^6\)\(^6\). 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 |          |       |                                             |                   |
| 37   | Marandi and Fatemi, 2019 | CPLEX | Imperialist Competitive Algorithm (ICA) |       |                                             |                   |
| 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 | GA | Local enhancement strategy | |
| 44   | Zhang et al., 2016 |          |          |       |                                             |                   |
| 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 | Iterated Greedy Algorithm (IGA) |          |       | Local search |                   |
| 50   | Zheng et al., 2020 | 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                                           | 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                                                                                 |
| 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)                    | Memory and neighborhood structures-based improving strategy                         |
| 73   | Rifai et al., 2016    | Adaptive Large Neighborhood Search (ALNS)                      | Collaboration mechanism, restart strategy                                           |
| 74   | Lei et al., 2020      | ICA                                                             | SA                                                                                  |
| 75   | Meng and Pan, 2020    | Constructive heuristics                                        | ABC                                                                                 |
| 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                                                                                  |
| 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 |
|------|-----------------|-----------------------|
| 84   | Meng et al., 2020 | CPLEX                 |
| 85   | Gong et al., 2020 | MA                    |
|      |                  | Swarm intelligence or evolutionary algorithm | Improving strategy |
| 86   | Lu et al., 2020  | Iterative Greedy (IG) |
| 87   | Wang et al., 2020 | Whale Swarm Algorithm (WSA) |
| 88   | Pan et al., 2020 | EA                    |
| 89   | Xiong et al., 2020 | NEH                  |
| 90   | J. Wang and L. Wang, 2018 | NEH |
|      |                  | Knowledge-based Cooperative Algorithm (KCA) |
| 91   | Fu et al., 2019  | BSO                   |
| 92   | Luo et al., 2020 | MA                    |
| 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 |
| 96   | Zhang and Gen, 2010 | GA                   |
| 97   | Giovanni and Pezzella, 2010 | GA |
| 98   | Gao and Chen, 2011 | NEH2                  |
|      |                  | GA and VND            |
| 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                    |
| 103  | Lu et al., 2018  | NEH adaptive (NEHA)   |
| 104  | Cai et al., 2018 | Nondominated Sorting Genetic Algorithm II (NSGA-II) |
| 105  | Wang et al., 2013 | Heuristics with SPT, LPT, and NEH |
|      |                  | EDA                   |
| 106  | Xu et al., 2014  | Immune Algorithm (IA) |
| 107  | Zhang et al., 2018 | VNS and Particle Swarm Optimization (PSO) |

(To be continued)
Table 4  Optimization approaches in the relevant literature.  

| 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  | Chaouche et al., 2017 | ACO      |           |       |                                              | Neighborhood strategy |
| 113  | Zhang and Xing, 2019 | 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 | ABC, SS and IGA      |           |       |                                              | Solution initialization with heuristics, reference local search |
| 116  | Lin et al., 2013 | NEH2                  |           |       |                                              |                   |
| 117  | Viagas and Framinan, 2015 | Bounded-search IGA  |           |       |                                              |                   |
| 118  | Ruiz et al., 2019 | NEH2_en based on NEH  | IGA       |       |                                              | Solution initialization based on a new NEH, 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 |       |                                              |                   |
| 121  | Deng and Wang, 2017 | NEH2                  |           |       |                                              |                   |
| 122  | J. Wang and L. Wang, 2020 |                   |           |       |                                              |                   |
| 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 |                   | Discrete ABC |       |                                              |                   |
| 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 |                   |           |       |                                              |                   |
3.1 SI and EAs

To address the highly complicated distributed scheduling problems, SI and EAs have been adopted, including GA\cite{38,39,44,51,88,93–104}, EDA\cite{50,81,105}, MA\cite{106}, VNS\cite{40,42,43,53,64,76,82,98,107–109}, TS\cite{43,55,89,110,111}, PSO\cite{107}, ACO\cite{35,112}, DE\cite{42,58,61,70,113}, SS\cite{114,115}, IGA\cite{49,50,55–57,59,63,80,82,83,86,89,108,109,115–120}, SA\cite{38,51,70,78}, MA\cite{65,66,85,92,121,122}, BBO\cite{67}, ICA\cite{37,39,74}, CRO\cite{123}, COA\cite{60}, FFO\cite{47}, TLBO\cite{124}, SSO\cite{69,71}, KCA\cite{90}, GWO\cite{41}, BSO\cite{46,91,125}, SFLA\cite{129,130}, ABC\cite{48,52,75,108,115,126–128}, IWO\cite{131}, WSA\cite{87}, WWO\cite{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:

1. Initialize the algorithm parameters and generate a set of solutions as a population.
2. Calculate the objective function values of solutions in the population.
3. Generate new solutions by adopting the solutions in the population.
4. Evaluate newly generated solutions and update the population.
5. If a given termination is reached, go to Step 6; otherwise, go to Step 3.
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 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 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...
Based on neighborhood structures\cite{73}, simulation\cite{45}, and multi-agent methods\cite{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\cite{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\cite{133-135} and improving processing quality\cite{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\cite{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\cite{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\cite{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\cite{146}. Distributed scheduling models can also be used to solve networking scheduling and control...
problems\cite{147}.

(5) Designing SI and EAs

Over the past years, SI and EAs have been successfully used to handle various complex optimization problems\cite{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.

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