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A survey of job shop scheduling problem: The types and models

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ABSTRACT

Job shop scheduling problem (JSSP) is a thriving area of scheduling research, which has been concerned and studied widely by scholars in engineering and academic fields. This paper provides a comprehensive review on the types and models of JSSP, to the best of our knowledge, there has not been a review paper on this aspect up to now. The main purpose of this review is to help researchers and scholars outlining an overview of existing JSSP models and exploring more valuable research directions. We first analyze and classify the entities and their attributes, assumptions, basic subtypes, and measures of performance of JSSP based on the researches from mid-1960s to 2020s. The general representation and overview of JSSP models are also presented. Then, some extensive statistics and analysis are conducted on 297 published papers in 72 journals ranging between 2016 and early 2021. Finally, some hot research aspects of JSSP models are reviewed in detail and some promising research directions are provided.

1. Introduction

The job shop scheduling problem (JSSP) is one of the most classical and important combinatorial optimization problems in the field of operational research and management science. For the extremely broad engineering and social application backgrounds, JSSP has been concerned and studied extensively by scholars in engineering and academic fields. A classical JSSP can be described as follows: in a job shop environment containing several machines $M = \{M_1, M_2, \cdots, M_m\}$, there are a number of jobs $J = \{J_1, J_2, \cdots, J_i, \cdots, J_n\}$, each job, say J_i, contains a serial of operations $O_i = \{O_{i1}, O_{i2}, \cdots, O_{ij}, \cdots, O_{in_i}\}$ which need to be processed in a predefined technological sequence. Each operation is assigned a machine in M to be processed with a given processing time p_{ij}. Sequencing need to be done for operations in all machines to minimize the maximum completing time of all jobs, i.e., to minimize the makespan.

JSSP is a kind of typical machine scheduling problem. The earliest machine scheduling problems found in the literature are two and three stage scheduling problems with setup times included (Johnson, 1954). For all the jobs have identical operations, the problems are corresponding to two and three machine flow shop scheduling problems, with the objective minimizing total elapsed time as the paper termed, i.e., minimizing the makespan. Akers (1956) and Akers and Friedman (1955) discuss a two parts (jobs) and four machines scheduling problem, each job has four operations, which need to, in different technological sequences, be processed on the four machines respectively. Hence, the problem can be viewed as a 2×4 JSSP. Then, Wagner (1959) addresses a scheduling problem with n items, each has different stages, and m machines; the problem corresponds to a $n \times m$ JSSP. A widely quoted description about schedule-sequencing is proposed by Bowman (1959) who presents a problem corresponding to 3×4 JSSP. Except for the research reports and discussion papers, Sisson (1959) should be the first scholar who gives the terminology "job shop" in the literature. In the paper, "job shop" is described as "Roughly, a job shop is characterized by the fact that the sequence of operations performed on any one lot or group of units to be fabricated is independent of the sequence required for any other lot." Thereafter, a huge amount of literature on machine scheduling, including job shop scheduling, has been published within the last six decades, among them some excellent review papers which can be referred to (Sisson, 1959; Mellor, 1966; Elmaghraby, 1968b; Day and Hottenstein, 1970; Panwalkar and Iskander, 1977; Graham et al., 1979; Graves, 1981; Green and Appel, 1981; Blackstone et al., 1982; Ramasesh, 1990; Sellers, 1996; Bazewicz et al., 1996; Allahverdi et al., 1999; Gordon et al., 2002; Allahverdi et al., 2008; Abdullah and Abdolrazzagh-Nezhad, 2014; Dhiflaoui et al., 2018; Xie et al., 2019b; Mohan et al., 2019; Gao et al., 2019). Here, We classify these review papers into three types: (1) the papers presenting a comprehensive survey (including models, approaches, algorithms, etc.) for multiple

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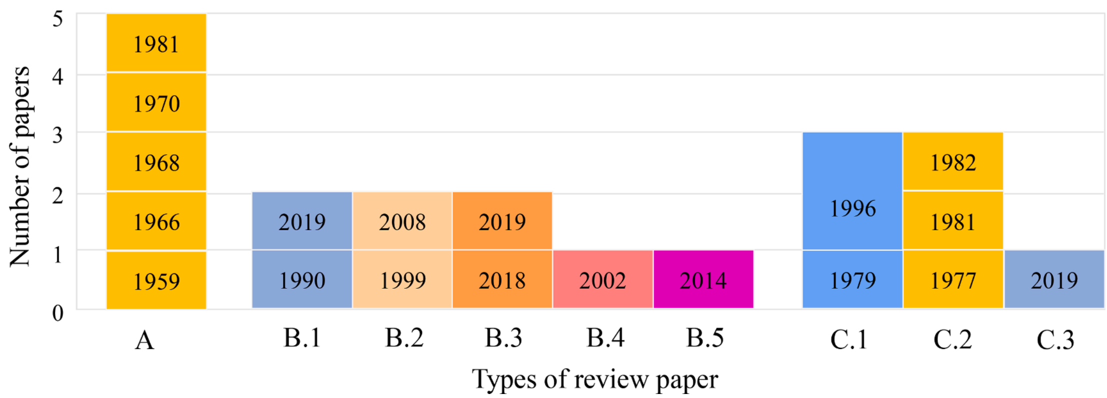

Fig. 1. The numbers of various types' review papers and the papers' publication years.

classes of scheduling problems, e.g., single machine scheduling, parallel machine scheduling, flow shop scheduling, and job shop scheduling, as which we call Type A; (2) the papers giving a comprehensive survey for only one kind of JSSP with one or more characteristic(s), as which we call Type B; (3) the papers conducting review work only with respect to the approaches and algorithms for shop scheduling problems, as which we call Type C. The numbers of these three types' review paper and the papers' publication years are presented in Fig. 1. In the figure, Type A, Type B and Type C are simply marked as A, B and C respectively. B.1 to B.5 denote the sub-division of B, corresponding to dynamic JSSP, JSSP with setup time and cost, flexible JSSP, JSSP with common due date, and fuzzy JSSP respectively. C.1 to C.3 denote the sub-division of C, where C.1 reviews both exact and approximate algorithms, C.2 concerns only the methods with priority rules or dispatching rules, and C.3 devotes to review swarm intelligence and evolutionary algorithms.

Type A papers mainly appeared in the early stage of scheduling problem research. They usually classify the scheduling problems into several types in a certain way first, and then review various solving approaches, algorithms and conclusions for these types of problems. The classification results are similar, though the factors considered and the angle of classification are different. According to the deterministic and stochastic characteristics, Sisson (1959) summarizes four categories of job shop problem, including mechanical model, mechanical models with stochastic properties, thermodynamic model and waiting-line approach. Then he discusses the corresponding solving methods respectively further. Elmaghraby (1968b) also points out that operational systems are either deterministic or stochastic and, as he says, for there existing some excellent summary and exposition of stochastic sequencing problems. Their reviews confine to deterministic machine sequencing problem. From the view of criteria in the objective function, Mellor (1966) puts the JSSP into two categories which are loosely described as the "minimum make-span" problems and the "due date" problems. Day and Hottenstein (1970) consider the classification of scheduling and sequencing problem from three fields, i.e., number of component parts comprising a job, production factors possessed by the shop, and jobs available for processing. In other words, these three fields actually correspond to non-assembly operation or assembly operation problems, single-resource constraint or dual-resource constraint problems, and static or dynamic scheduling problems respectively. Graves (1981) classifies production scheduling problems in three dimensions: (1) Requirements generation. With this dimension, a production scheduling problem is either open-shop or closed-shop, depending on the production tasks which are from customers' orders or inventory replenishment. (2) Processing complexity. For this dimension, the problems can be decomposed into one-stage-one-processor, one-stage-parallel processors, multistage-flow shop, and multistage-job shop. (3) Scheduling criteria. With respect to this dimension, the scheduling problem can be divided into schedule-cost criteria problems and schedule performance criteria problems. Take their categories as the main line, these Type A papers all give the review with respect to the corresponding approaches, algorithms and conclusions further.

For Type B papers, Ramasesh (1990) and Mohan et al. (2019) conduct comprehensive reviews with the dynamic JSSP (B.1 in Fig. 1). Excellent reviews on JSSP with setup time and/or setup cost (B.2 in Fig. 1) have been given by Allahverdi et al. (1999) and Allahverdi et al. (2008). Flexible JSSP (B.3 in Fig. 1) is also a kind of widely concerned problem. The related survey researches are conducted by Dhiflaoui et al. (2018) and Xie et al. (2019a). The flexible JSSPs in Dhiflaoui et al. (2018) mainly focus on dual-resource constraint problems. Gordon et al. (2002) conduct a survey for the common due date scheduling problems (B.4 in Fig. 1), and a review on fuzzy job-shop scheduling problems (B.5 in Fig. 1) is presented by Abdullah and Abdolrazzagh-Nezhad (2014).

The issues on solving approaches and algorithms for shop scheduling problems seem to be also the popular review research topics. In a general way, algorithms for scheduling problems can be grossly classified into two categories: exact algorithms and approximate algorithms. Some papers' reviews cover both the two categories (C.1 in Fig. 1), an earlier corresponding paper can be referred to Graham et al. (1979). Bazewicz et al. (1996) survey exact methods with their emphasis on branch and bound; and with respect to approximate algorithms, their work contains priority rule, shifting bottleneck heuristic, opportunistic scheduling, local search, constraint propagation, and ejection chain. In the research of Sellers (1996), the solving algorithms fall into three classes: heuristic rules, classical optimization methods (mainly referring to branch and bound method and dynamic programming), and neural network approaches. Scheduling rules, also named dispatching rules or priority rules, are popular and effective for solving various scheduling problems, especially for dynamic and complicated scheduling problems. The corresponding review researches (C.2 in Fig. 1) are referred to Panwalkar and Iskander (1977), Green and Appel (1981), and Blackstone et al. (1982). Swarm intelligence and evolutionary algorithms (C.3 in Fig. 1) are also widely used to solve various scheduling problems. Gao et al. (2019) conduct the corresponding review work for the flexible JSSP.

On the whole, from the above review papers, we can draw the following conclusions:

(1) For the more and more attention paid to scheduling problems, and vigorous growth of the number of scheduling related papers, it is very difficult to conduct comprehensive survey for all kinds of scheduling problems. Hence, with the exception of some earlier (before 1980s) related review papers, most of scheduling related review literature is only focus on a kind of scheduling problem (e.g. dynamic JSSP) or an issue (e.g. algorithm) about scheduling problem.
(2) With the rapid development of scheduling problem solving algorithms, more and more effective algorithms are presented. Therefore, when some review issues are concerned, solving methods and algorithms are almost the popularly selected ones.

(3) Compared with the types of scheduling problem solving algorithms, the types of scheduling problem models are much less. The classifications of scheduling problem models in the literature are broad and roughly the same; and, to the best of our knowledge, there has not been a review paper on the model of scheduling problem up to now.
(4) With the number of related researches increases, the practical engineering and social application backgrounds involved researches are more and more. Besides, there are more and more detailed characteristics of scheduling problems reported in the literature correspondingly. These detailed characteristics reflect some essential differences in the nature of scheduling problems. So, based on the related survey literature, it is a great significance to the overall understanding of the research status of scheduling problems by analyzing and summarizing the types and characteristics of scheduling problems from a more detailed point of view.

The above facts and analyses motivate us to conduct the work of this paper. In this paper, we restrict our concern only on some aspects of the models of scheduling problem, including the problem characteristics, the problem classifications, the corresponding statistical analyses, and several hot research issues on the models of scheduling problem. In consideration of the sheer volume of related literature, in this paper, the time horizon of the literature considered in the analyses and statistics is confined to the last five years, i.e., from 2016 to early 2021. Though the time span is short, the absolute number of the literature included is large and, in addition, the research contents have a good coverage, representativeness and statistical significance.

The organization of the remaining sections of this paper is as follows. In Section 2, we detailedly analyze and list the entities and their attributes, assumptions, and common basic subtypes of JSSP. An analysis and classification with the objectives of JSSP in the literature is given in Section 3. In Section4, the general representation and overview of JSSP models is presented. In Section 5, comprehensive statistics and analysis for the related literature are provided. Several hot research issues on the models of JSSP are reviewed in Section 6. Finally, Section 7 draws some conclusions and provides guidelines for future research.

2. Entities, assumptions, and basic subtypes of JSSP

2.1. Entities and their attributes in JSSP

As with other classes of machine scheduling problems, there are two necessary entities in JSSP. One is the tasks to be processed (e.g. mechanical parts, electronic components, or other items), which are usually and hereinafter in this paper called as jobs; and the other one is the facilities used to process jobs, which are usually and hereinafter in this paper called as machines. In addition to these, in the production activities of manufacturing systems, there may usually involves one or more of the following entities: operators, transportation devices, industrial robots, auxiliary tools and appliances, warehouses, buffers, and containers, all of which are collectively called supplementary resources in this paper. In some researches, one or more of these supplementary resources may be explicitly considered into the models of scheduling problem. With a view to influencing the characteristics of the scheduling problem model, we present a detailed analysis to the entities and their attributes.

For the entity "job", following attributes are considered: time attributes, categorical attribute, batch attribute, weight attribute, technological attribute, and release and delivery mode attributes. In terms of the entity "machine", the attributes include functional attribute, availability, categorical attribute, affiliation attribute, energy consumption attribute, and carbon emission attribute. Some attributes, with which we regard as "job-machine" associate attributes, are related to not only "job" but also "machine", e.g., processing suitability, processing model,

Table 1
The entities, the corresponding attributes, and their options or values in JSSP.

Entity	Attribute	Options or Values
Job	Release time	Zero; Arbitrarily given; Poisson process; Gaussian distribution; Uniform distribution
	Due date	Na; Arbitrarily given; Given by rules
	Processing time	Deterministic value; Processing time deterioration*; Variable processing time*; Controllable processing time*; Obey random distribution; Fuzzy value; Interval value; Machine-Dependent processing time
	Auxiliary time	Without consideration; Sequence-independent setup time; Sequence-dependent setup time; Transportation time*
	Categorical attribute	Without consideration; Different families of jobs
	Batch attribute	No batch; batch consideration
	Weight attribute (priority)	Without consideration; Given weight; With prior job*; Urgent job*
	Technological attribute	Single routing; Alternative routing*
	Release mode	Single release; batch release
	Delivery mode	Single delivery; Equal size batch delivery; Given size batch delivery; Batch delivery by decision; Whole batch delivery
Machine	Functional attribute	Uni-functional machine; Multifunctional machine*
	Availability	Always-available; Random failure; Random maintenance*; Regular maintenance*; Condition based maintenance*
	Categorical attribute	Without consideration; Different groups of machine
	Affiliation attribute	Without consideration; Affiliated with different line*; Affiliated with different cell*; Affiliated with different factory*
	Energy consumption attribute	Without consideration; With consideration
	Carbon emission attribute	Without consideration; With consideration
Job-Machine	Processing suitability	No path flexibility; Full path flexibility#; Partial path flexibility
	Processing model	Single machine single job; Batch processing; Multiprocessor processing#
	Processing successive attribute	Waitable; No-wait*
	processing preemption	Non-preemptive; Preemptive#
	Processing reentrancy	No reentrancy; Reentrancy*
	Processing overlap	Non-overlapping; Overlapping#
Supplementary resources	Operator-involved	Without operator consideration; Operator consideration*(Dual resource constraint)
	Robot-involved	Without robot consideration; Robot consideration*
	Buffer size	Infinite buffer; Limited buffer#; No buffer (Blocking)*
	Other supplementary resources	Without consideration; Limited capacity warehouse#; With auxiliary tool and appliance consideration#; With container consideration#

processing successive attribute, processing preemption attribute, processing reentrancy attribute, and processing overlap attribute. With respect to supplementary resources, the main attributes are operator-involved attribute, robot-involved attribute, buffer size, auxiliary tool and appliance-involved attributes, and container-involved attribute. All these attributes of the entities and their options or values are listed in

Table 2
Assumptions in JSSP models.

Mark	Description
AC1	All jobs are released at time zero for processing. The number of jobs is pre-known and fixed. No job is permitted to be canceled during processing.
AC2	All machines are available at time zero.
AC3	All jobs have the same weight.
AC4	All jobs do not specify due dates.
AC5	There is no arbitrary priority among different jobs.
AC6	Each operation is given a unique and predetermined processing time.
AC7	Each job is specified previously a unique and fixed processing routing, i.e., technological sequences among operations of a job.
AC8	Jobs are independent from one another, i.e., there are no precedence constraints among the operations of different jobs.
AC9	Each operation can only be pre-assigned to only one machine for processing, i.e., no path flexibility is considered.
AC10	An operation of a job can be performed by only one machine at a time, i.e., no multiprocessor case is considered.
AC11	Each machine can perform only one operation at a time on any job, i.e., no batch processing is considered.
AC12	Waiting is permitted between the processing of adjacent operations on the same job.
AC13	Machines are independent of each other.
AC14	Once an operation is started, it must be completed without interruption.
AC15	Once an operation is started, it must be completed without preemption.
AC16	No reentrancy is not considered, i.e., a job does not visit the same machine twice or more.
AC17	Setup times of machines and transit times between operations are negligible, i.e., these times are assumed to be included in the operations' processing time.
AC18	All machines are continuously available without consideration of machine breakdown and maintenance.
AC19	Re-processing for unqualified jobs and insertion of emergency jobs are not considered.
AC20	No operator constrain is considered.
AC21	Capacities of buffer, warehouse and container are not considered or assumed to be unlimited; auxiliary tool and appliance are always available.

Table 1.

In Table 1, the following points need to be explained additionally: (1) for the attribute of release time, the option "arbitrarily given" means that jobs' release times are given nonzero values arbitrarily. For the release times are deterministic and known, the corresponding JSSP is a type of static scheduling problem rather than a dynamic scheduling problem. (2) the options/values attached with the superscript of asterisk are mainly appeared in the JSSP models of the recent literature. (3) though the options/values attached with the superscript of pound sign have hardly been seen in the literature, however, we list them in the table in consideration of the completeness of options.

2.2. Assumptions or constraints of JSSP

In the model of classical (ordinary, general) JSSP, there are usually a set of assumptions or constraints. In essence, whether calling them assumptions or constraints, the literature means the differences of some characteristics between the reality and the model, or means the simplifications or idealizations of the model to the actuality. So, the literature usually does not make the distinction between them. For the sake of simplicity and consistency, hereafter in this paper, we call all the differences, simplifications and idealizations as assumptions. Here in the Table 2, we present the various assumptions or constraints in the literature.

In the literature, AC14 and AC15 are usually regarded as the same and both called the non-preemptive constraint. Here in this paper, we call AC14 as continuous processing constraint, which means that the processing of an operation must be continuous from its start to finish, without interruption for machines breakdown, operators' rest, and holidays; and we call AC15 as non-preemptive constraint, which mainly means that the processing of an operation should not be interrupted by another operation. It's not hard to understand that, considering the unexpected breakdown of machines during processing and the rest time, non-preemptive constraint doesn't necessarily satisfy the continuous processing constraint. Given any two different operations O_{ij} and $O_{i'j'}$, their start times, finish times, and processing times are denoted as s_{ij}, c_{ij}, p_{ij}, $s_{i'j'}$, $c_{i'j'}$, and $p_{i'j'}$, continuous processing constraint can be formulated as $c_{ij} = s_{ij} + p_{ij}$; while, non-preemptive constraint are satisfied by $max\{s_{ij}, s_{i'j'}\} \geq min\{c_{ij}, c_{i'j'}\}$.

2.3. Common basic subtypes of JSSP

Based on the different options or values of the attributes listed in Table 1, we can classify the JSSP into a set of types. The attributes of entities are the principal elements reflecting the characteristics and differences of a JSSP model. Furthermore, anyone of the criteria can usually be applied to various JSSP model. In this paper, we conduct the classification of JSSP only considering the different options or values of the attributes.

(1) Classical JSSP: a classical JSSP is the most basic JSSP, in which all the assumptions in Table 2 are involved.

(2) Dynamic JSSP: in static JSSP, all involved attributes of the entities and related workshop environment information are pre-known and always remain unchanged during the scheduling process; otherwise, a JSSP is defined as dynamic JSSP (DJSSP). A DJSSP relaxes one or more of the assumptions AC1, AC4, AC6 and AC19. With respect to the changed attributes of entities or information of workshop, DJSSP can be further classified into some subtypes as follows.

- The subtypes related to the change of time attributes of jobs: processing times of operations change (AC6), due dates of jobs change (AC4);
- The subtypes related to the change of number of jobs: jobs arrive at shop consecutively (AC1), emergency jobs insert into processing queue accidentally (AC19);
- The subtypes related to the change of jobs' qualities: unqualified jobs are assigned to re-processed (AC19).

(3) JSSP considering the machine state (or the machine availability): this type of JSSP relaxes the assumption AC18. From the view of information changes during the scheduling process, JSSP considering the machine state belong to DJSSP. However, in some researches, a static JSSP may also consider the machine breakdown and/or maintenance. As to periodic or regular machine maintenance, the maintenance activity is prepense and pre-known even though the machine state changes. In this paper, we classify the JSSP considering the machine state as another type of JSSP rather than DJSSP. The unavailable state of machines includes the machine breakdown and maintenance, and the machine maintenance can be further divided into two classes: periodic or regular machine maintenance, and condition-based maintenance.

(4) Flexible JSSP: the flexible JSSP (FJSSP) can be classified into two types: FJSSP with alternative routings, relaxing AC7, and FJSSP with alternative machines, relaxing AC9. The former is characterized by technological flexibility, namely technological flexibility JSSP (TFJSSP), and the latter is characterized by path flexibility, namely path flexibility JSSP (PFJSSP). With respect to the processing machine set of an operation, PFJSSP can be further divided into partial path flexibility JSSP (PPFJSSP), the processing machine set being a subset of all machines, and complete path flexibility JSSP (CPFJSSP), the processing machine set being the set of all machines. With respect to the processing time, PFJSSP can be further divided into that with machine-independent processing times and that with machine-dependent processing times.

Table 3
The JSSP basic types, subtypes, codes, and relaxation assumptions.

JSSP basic types	Subtypes	Codes	Relaxation
Classical JSSP		ST1	Na
Dynamic JSSP (DJSS)	Related to time attributes of jobs	ST2	AC6
	Related to the number of jobs	ST3	AC1, AC19
	Related to qualities of jobs	ST4	AC19
JSSP considering the machine availability	Considering machine breakdown	ST5	AC18
	Considering periodic maintenance	ST6	AC18
	Considering state-based maintenance	ST7	AC18
Flexible JSSP (FJSS)	PPFJSSP with machine-independent processing times	ST8	AC9
	PPFJSSP with machine-dependent processing times	ST9	AC9
	CPFJSSP with machine-independent processing times	ST10	AC9
	CPFJSSP with machine-dependent processing times	ST11	AC9
	TFJSSP	ST12	AC7
JSSP considering batches	parallel batch JSSP	ST13	AC11
	batch decision JSSP	ST14	Na
JSSP considering setup times	JSSP with sequence-dependent setup time	ST15	AC17
	JSSP with sequence-independent setup time	ST16	AC17
JSSP with nondeterministic or nonconstant processing time	With start time-dependent deteriorating jobs	ST17	AC6
	With controllable processing times	ST18	AC6
	With random distribution processing times	ST19	AC6
	With fuzzy processing times	ST20	AC6
Distributed JSSP (DSJSSP)	DSJSSP in different cells	ST21	Na
	DSJSSP in different lines	ST22	Na
	DSJSSP in different factories	ST23	Na
JSSP with dual-resource constraints (DRJSSP)	Considering availabilities of machines and operators	ST24	AC20
JSSP considering energy and pro-environment	JSSP with energy consumption related criteria	ST25	Na
	JSSP with carbon footprint related criteria	ST26	Na
	JSSP with noise emission related criteria	ST27	Na
JSSP less studied in the literature	JSSP with prior job	ST28	AC5
	JSSP with dependent jobs	ST29	AC8
	JSSP with no-wait constraint	ST30	AC12
	JSSP with blocking constraint	ST31	AC21
	JSSP with reentrancy	ST32	AC16
	JSSP with premeptibility	ST33	AC15
	JSSP considering overtime work	ST34	Na
	JSSP with limited buffer capacity	ST35	AC21
	JSSP considering outsourcing (subcontracting)	ST36	Na
	JSSP considering robot or automated guided vehicle (AGV)	ST37	Na

(5) JSSP considering batches: this type of JSSP can be classified into two very different kinds of problems. One, relaxing AC11, is usually called parallel batch problem, in which there are some batching machines allowing multiple jobs to be processed on them simultaneously. The other considers batch release and/or batch delivery, which is usually called batch decision scheduling problem.

(6) JSSP considering setup times: this type of JSSP relaxes the assumption AC17, which is usually be classified into the JSSP with sequence-independent setup time and the JSSP with sequence-dependent setup time. The JSSP with sequence-dependent setup time actually corresponds to explicit consideration of both the setup time and the removal time for an operation.

(7) JSSP with nondeterministic or nonconstant processing time: this type of JSSP relaxes the assumption AC6, which can be classified into the JSSP with start time-dependent deteriorating jobs, the JSSP with controllable processing times, the JSSP with fuzzy processing times, and the JSSP with random distribution processing times.

(8) Distributed JSSP (DSJSSP): in this type of JSSP, machines belong to different geographical regions, e.g., different cells, different lines, or different factories. Compared with a classical JSSP, the DSJSSP should make an additional decision to assign a job to which region's machine for processing. In addition, transport times and costs may also be the factors to be considered due to the allopatric character of machines.

(9) JSSP with dual-resource constraints: in classical JSSP, for an operation, the machine is the only processing resource required, i.e., as long as the machine is available, the corresponding operator defaults to be available. However, JSSP with dual-resource constraints, relaxing the assumption AC20, involves explicitly the operator into the processing resource, i.e., only corresponding machine and operator are both available, can an operation be processed. This type of JSSP needs to conduct not only machine scheduling but also operator scheduling.

(10) JSSP considering energy and pro-environment: in classical JSSP, energy consumption and emissions are not taken as decision-making criteria. In recent years, however, with the strengthening of people's awareness of energy conservation and environmental protection, as well as the transformation and improvement of production modes, manufacturing concepts, and their pursued goals, some researches of scheduling problems have been conducted to incorporate energy conservation and environmental protection criteria into scheduling decisions. It is reasonable to speculate that this type of JSSP should become an important development direction of follow-up researches.

(11) Others: in addition to the above types, there are some types of JSSPs, which is relatively less studied in the literature, e.g., JSSP with prior job (relaxing AC5), JSSP with dependent jobs (relaxing AC8), JSSP with no-wait constraint (relaxing AC12), JSSP with blocking constraint (relaxing AC21), JSSP with reentrancy (relaxing AC16), JSSP with premeptibility (relaxing AC15), JSSP with limited buffer capacity (relaxing AC21), JSSP considering outsourcing (subcontracting), and JSSP considering overtime work.

The above-mentioned various basic types, corresponding subtypes, the codes, and the relaxed assumptions or constraints are shown in Table 3.

3. Measures of performance in JSSP

The objective of scheduling is to optimize one or more measures of performance related to the revenue of the manufacturing system, which is an important aspect to present the characteristics of scheduling problem model. In regard of measures of performance, Mellor (1966) classifies the JSSP into two categories: the "minimum make-span" problem and the "due date" problem. Ramasesh (1990) summarizes four types of measures, i.e., time-based measures, work-in-process measures,

Table 4
The elementary criteria involved in the objectives of scheduling JSSP models.

Type of criterion	Criterion	Code of Criterion	Tendency to pursue
Time-based	Makespan	CR1	minimized
	Sum of (weighted) completion time	CR2	minimized
	Sum of (weighted) earliness	CR3	minimized
	Sum of (weighted) tardiness	CR4	minimized
	Sum of (weighted) earliness and tardiness	CR5	minimized
	Sum of (weighted) idle time of all machines	CR6	minimized
Job-number-based	Sum of tardy jobs	CR7	minimized
	Percentage of tardy jobs	CR8	minimized
	Number of jobs in stock	CR9	minimized
	Number of jobs in process	CR10	minimized
Cost-based	Processing cost	CR11	Minimized
	Logistics cost	CR12	minimized
	Stock-holding cost	CR13	minimized
Revenue-based	(weighted) Machine utilization	CR6	maximized
	Total revenue of production	CR14	maximized
Energy and pro-environment-based	Total energy consumption*	CR15	minimized
	Carbon footprint*	CR16	minimized
	noise emission	CR17	minimized

due-date related measures, and cost-based measures. In this paper, from the view of the characteristics of parameters involved in the criteria, we classify the measures of performance (i.e., criteria) into five types: time-based criteria, job-number-based criteria, cost-based criteria, revenue-based criteria, and energy and pro-environment-based criteria. With regard to the tendencies that the objective pursue, the criteria can be divided into maximized ones and minimized ones. Based on the above classification schemes, the elementary criteria in the objectives of the related literature are listed in Table 4.

In Table 4, what needs to be additionally remarked are described as follows:

(1) The criteria listed in the table are elementary and frequently-used. Some criteria in the literature may not appear in the table, however, these criteria are equivalent to some ones in the table. For example, penalty of earliness and penalty of earliness tardiness, without appearing in the table, are evidently equivalent to earliness and tardiness respectively.
(2) Some criteria in the table are correlative, e.g., number of jobs in stock and stock-holding cost, sum of (weighted) idle time of all machines and (weighted) machine utilization.
(3) The items attached with the superscript of asterisk are mainly appeared in the recent research literature.

4. The general representation and overview of JSSP models

Combining the description of Section 2 and Section 3, we can construct various JSSP models by different entities and criteria. The three-field notation $\alpha|\beta|\gamma$ (Graham et al., 1979) is one of the most commonly used methods to describe a scheduling problem. The first field (i.e., α) represents the shop environment. Generally, the JSSP is usually denoted by "J". The second field (i.e., β) describes job characteristics and scheduling constraints. The third field (i.e., γ) defines the performance measure. The classification in Table 3 can well reflect the characteristics of the first field and second field, while the elementary criteria in Table 4 are widely used objective function of the third field. For example, a preemptive JSSP to minimize makespan can be noted as $J|pmtn|C_{max}$.

Over the past six decades, JSSP has been extensively studied since it was first addressed by Johnson (1954). Then, it attracts the interests of both academic researchers and practitioners. A large number of literature on JSSP has been published every year. Fig. 2 shows an overview of some typical papers on various JSSP models from 1960s to 2020s. Among them, some are the earliest relevant papers in each of the topics. Johnson (1954) is the earliest study reported addressing the machine scheduling problem. Barlow and Hunter (1960) is the first to study preventive maintenance policies (refer to ST5, ST6, ST7). They introduce two preventive maintenance policies, one which is to repair at the time of failure and another which is to do maintenance activity after a certain number of operating hours. Elmaghraby (1968a) is one of the earliest researches on the "related" jobs (refer to ST28, ST29). The jobs are not independent in his study, they are "related" to each other in a pairwise fashion. Wilbrecht and Prescott (1969) conduct a study to determine the influence of setup time on job shop performance. They choose seven priority rules for experiment and introduce some assumptions based on experience with an electronics company and published literature.

From Fig. 2, we can roughly find the progress of the research on JSSP models. Almost all the JSSP types listed in Table 3 have been addressed between mid-1960s and 2000s. In the real world manufacturing environment, the processing time is usually uncertain rather than in an

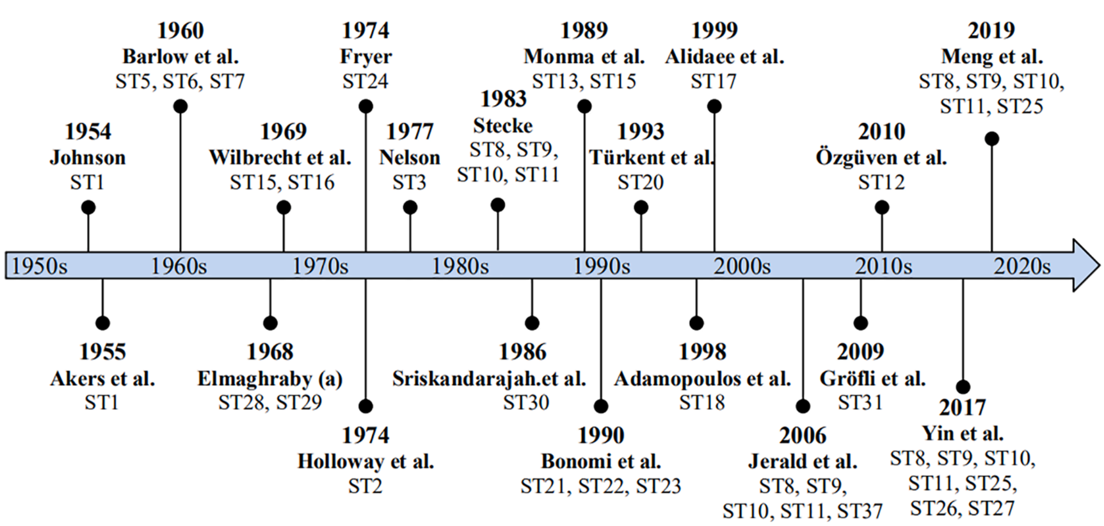

Fig. 2. Timeline showing some typical papers on various JSSP models.

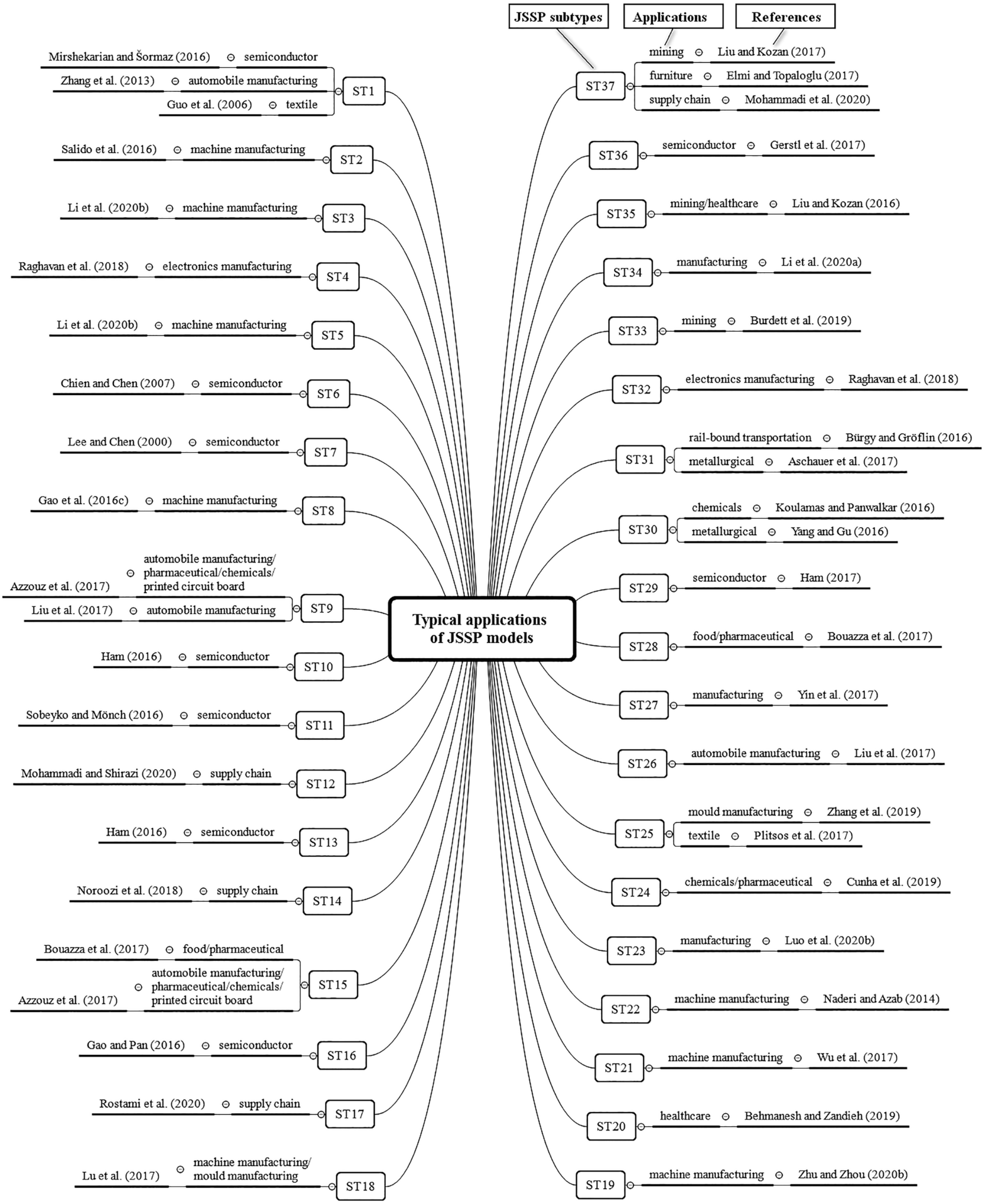

Fig. 3. Typical applications of JSSP models.

accurate value. Adamopoulos and Pappis (1998) utilize a neighbourhood-based hybrid method to solve a single machine scheduling problem with fuzzy due-dates and controllable processing times. Holloway and Nelson (1974) develop a multi-pass heuristic scheduling procedure for JSSP with processing times are random variables. The fuzzy logic is usually used to give job releasing and job dispatching decisions (Türkent et al., 1993). Besides, Alidaee and Womer (1999) conduct a review of single machine scheduling with time dependent processing times. Many practical JSSPs involve considering batch processing and setup time. Monma and Potts (1989) extend various scheduling models to include batch setup times and classify these problems as efficiently-solvable or NP-hard. Machines and workers are two main resources in the shop. Fryer (1974) describes a simulation study of the effects of labor flexibility on the performance of a multi-echelon dual-constraint job shop. They find that labor flexibility has a major effect on shop performance. Dynamic events are often considered in JSSP. For example, Nelson et al. (1977) propose centralized scheduling and priority implementation heuristics for dynamic JSSP with newly arriving jobs. Affected by the globalization of the market environment, the rapidly changes in customers' needs, and the development of science and technology, new corresponding JSSP models are introduced. Driven by the industrial artificial intelligence and rising manufacturing costs, AGV and robot have been widely used in shop floor to improve the production efficiency and reduce costs. Jerald et al. (2006) consider the parts and AGVs scheduling simultaneously in a flexible manufacturing system. They propose a non-traditional adaptive genetic algorithm to solve the problem. With the rapid development of globalization and competitive industrialization, many manufacturing enterprises shift the production mode from the traditional centralized single-factory mode to the distributed mode. Bonomi and Kumar (1990) propose a nonhomogeneous multi-server system with a central job scheduler. They present an adaptive optimal load balancing policy to allocate the "generic jobs" to the proper server. The research on machine flexibility (Stecke, 1983; Jerald et al., 2006; Yin et al., 2017; Meng et al., 2019) is more than routing flexibility (Özgüven et al., 2010). For current decade, the environmental and energy crises have become worldwide problems that have attracted a increasing attention in most fields. More and more papers related to the energy and pro-environment-based topics in the scheduling field have been reported. Yin et al. (2017) formulate a new low-carbon mathematical scheduling model for FJSSP. A multi-objective genetic algorithm is also proposed to solve this problem with optimizing productivity, energy efficiency and noise reduction. Meng et al. (2019) address a FJSSP with the objective of minimizing total energy consumption. There are some types of JSSPs are relatively less studied in the literature. Such as JSSP with blocking constraint (Gröflin and Klinkert, 2009) and JSSP with no-wait constraint (Sriskandarajah and Ladet, 1986).

Due to its great application value, JSSP has always been a hot research field for several decades. Fig. 3 presents some typical applications of JSSP models. From the figure, we can find that JSSP is widely applied in semiconductor (Lee and Chen, 2000; Chien and Chen, 2007; Ham, 2016; Mirshekarian and Šormaz, 2016; Sobeyko and Mönch, 2016; Gao and Pan, 2016; Gerstl et al., 2017), machine manufacturing (Naderi and Azab, 2014; Gao et al., 2016c; Salido et al., 2016; Li et al., 2020b; Zhu and Zhou, 2020b;), automobile manufacturing (Zhang et al., 2013; Azzouz et al., 2017; Liu et al., 2017;), supply chain (Noroozi et al., 2018; Mohammadi et al., 2020; Rostami et al., 2020; Mohammadi and Shirazi, 2020), metallurgical (Yang and Gu, 2016), textile (Guo et al., 2006), etc. These models are strongly related to the characteristics of the corresponding application fields. Fore example, chemicals, pharmaceuticals and food have high requirements for timeliness and precedence constraints, the models of ST15 (Azzouz et al., 2017), ST28 (Bouazza et al., 2017), ST30 (Koulamas and Panwalkar, 2016) are then appeared. From Fig. 3, we can find that these JSSP models have also been used in areas that were relatively rare before. Liu and Kozan (2017) and Burdett et al. (2019) utilize the JSSP models to mining field. Elmi and Topaloglu (2017) propose a JSSP with multiple robots. The problem is arisen from a modern furniture factory.

5. Statistics and analysis of the types and models of JSSP

5.1. Scope of the review literature

A comprehensive literature survey was conducted from database of Web of Science, Elsevier, Springer, ACM, etc. We confine the scope of the review paper to the last five years for the detailed statistics and analysis. This is because of several reasons. First, there are too many papers on JSSP. If the time span is too long, the review work will be too heave to complete. Second, the literature reviewed in previous sections is collected from mid-1960s to date, which has a good coverage. Third, we aim to review the up-to-date JSSP models to identify the current research focus and challenges in next sections. Therefore, about 300 published papers in 72 journals ranging from 2016 to early 2021 are selected in our next discussion. The number of papers that published each year is presented in Table 5. There more than 45 papers are collected per year.

Table 5
Distribution of reviewed papers between 2016 to early 2021.

Year	Number of Papers	Percentage
2016	61	20.54 %
2017	48	16.16 %
2018	45	15.15 %
2019	61	20.54 %
2020	66	22.22 %
2021	16	5.39 %
Total papers	**297**	**100 %**

5.2. Detailed statistics and analysis of the literature

Combining the JSSP basic subtypes listed in Table 3 with the elementary criteria listed in Table 4, we can construct various basic JSSP models. For 37 basic subtypes and 17 elementary criteria, 629 basic JSSP models can be gotten, e.g., combining ST33 with CR1, we forming a preemptive JSSP with makespan being the scheduling objective denoted as $J|pmtn|C_{max}$ in the three fields notation. In Table 6, we give the numbers of literature in which the studies are related to various basic JSSP types with different elementary criteria.

It's important to note that:

(1) Scheduling models in many researches can be viewed as the combinations of several basic subtypes in Table 3 (e.g., Ham (2016) considers a flexible JSSP with parallel batch processing machines, corresponding to the combination of ST9 and ST13), hence, the numbers of literature for all the related elementary subtypes (i.e., ST9 and ST13) are conducted for the corresponding accumulations.
(2) With respect to the scheduling objective, many researches consider one elementary criterion or multiple objectives consisting of several elementary criteria (e.g., CR1 and CR4 in the study conducted by Knopp et al. (2017), CR1, CR15, and CR17 in the study conducted by Yin et al. (2017)). For these cases, we also give the corresponding accumulations for all the related elementary criteria.

In Table 6, the rows and columns represent basic subtypes and elementary criteria of JSSP respectively. Here we also have visualized the summation of each row and column using plot, as depicted in Figs. 4 and 5.

Based on the data in Table 6, some conclusions can be summarized as follows:

(1) Classical JSSP model (i.e., ST1) is useful in understanding the scheduling problem and helpful for developing solutions which can be tested to determine whether they are better than existing approaches for the problem. So this model has always drawn the attention of many researchers. Wang et al. (2016b) and Kurdi (2016) propose new approaches based on genetic algorithm for JSSP. Cheng et al. (2016a), Kuhpfahl and Bierwirth (2016), Nagata and Ono (2018), Wang et al. (2018d), Wang et al. (2018a)

Table 6
Number of literature that relate to various basic JSSP types and criteria.

Type	CR																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	SUM
ST1	32	7	2	14	2	2	2	1	0	0	1	1	0	2	2	0	0	**68**
ST2	3	2	0	2	2	0	0	0	0	0	1	0	0	0	0	0	0	**10**
ST3	13	8	0	7	1	1	1	0	0	1	0	0	0	0	2	0	0	**34**
ST4	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**4**
ST5	11	5	0	1	2	2	0	0	0	1	1	0	0	0	2	0	0	**25**
ST6	10	6	0	2	0	3	0	0	0	0	2	0	0	0	2	0	0	**25**
ST7	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
ST8	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**4**
ST9	106	15	0	19	4	27	1	0	0	0	11	0	1	0	25	4	3	**216**
ST10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
ST11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
ST12	17	4	0	2	1	3	0	0	0	0	2	0	1	1	0	1	0	**38**
ST13	14	4	1	5	1	1	1	0	0	0	4	0	2	0	2	0	0	**35**
ST14	1	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	**4**
ST15	21	5	1	4	1	2	1	0	0	1	4	0	2	3	2	1	0	**50**
ST16	6	2	0	4	0	2	0	0	0	0	2	0	1	1	2	1	0	**21**
ST17	4	1	1	1	1	0	1	0	0	0	0	0	0	0	1	0	0	**12**
ST18	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**4**
ST19	1	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	**5**
ST20	7	0	1	1	0	1	0	0	0	0	1	0	2	0	0	0	0	**13**
ST21	5	1	0	1	0	0	0	0	0	0	2	0	1	1	0	0	0	**11**
ST22	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
ST23	7	1	0	0	0	1	0	0	0	0	0	0	0	0	2	1	0	**12**
ST24	12	2	0	2	1	2	0	0	0	1	4	0	1	0	3	0	1	**29**
ST25	27	2	0	8	1	8	0	0	0	0	8	0	1	0	39	4	3	**103**
ST26	6	0	0	1	0	2	0	0	0	0	0	0	0	0	3	6	1	**19**
ST27	3	0	0	0	0	0	0	0	0	0	1	0	0	0	4	1	3	**12**
ST28	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**5**
ST29	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**2**
ST30	14	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	**18**
ST31	7	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**8**
ST32	4	1	0	1	0	1	0	0	0	0	1	0	0	0	1	0	0	**9**
ST33	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
ST34	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	**2**
ST35	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
ST36	2	0	0	0	0	0	0	0	0	0	2	0	1	1	0	0	0	**6**
ST37	11	5	0	2	2	3	0	0	0	0	2	1	0	1	1	0	0	**28**
SUM	**364**	**78**	**6**	**81**	**22**	**61**	**8**	**1**	**0**	**4**	**51**	**3**	**13**	**12**	**94**	**19**	**11**	

Notes. The references cited in this table are (Li et al., 2016b; Fitouri et al., 2016; Salido et al., 2016; Kemmoé et al., 2016; Cheng et al., 2016b; Xia et al., 2016; Hart and Sim, 2016; Ahmadi et al., 2016; Jin et al., 2016; Teekeng et al., 2016; Pérez and Raupp, 2016; Ning et al., 2016; Cheng et al., 2016a; Asadzadeh, 2016; Maroosi et al., 2016; Singh and Mahapatra, 2016; Gao and Pan, 2016; Kuhpfahl and Bierwirth, 2016; Hsu et al., 2016; Li et al., 2016a; Wang et al., 2016b; Scaria et al., 2016; Li and Gao, 2016; Kurdi, 2016; Kundakcı and Kulak 2016; Gao et al., 2016b, Pranzo and Pacciarelli, 2016; Bekkar et al., 2016; Kaplanŏglu, 2016; Liu et al., 2016; Gao et al., 2016c; Tang et al., 2016; AitZai et al., 2016; Tempelmeier and Copil, 2016; Shen and Zhu, 2016; Tan et al., 2016; Mirshekarian and Šormaz, 2016; Gao et al., 2016a; Alotaibi et al., 2016; Akram et al., 2016; Ham, 2016; Sobeyko and Mönch, 2016; Nouri et al., 2016b; Yue et al., 2016; Choi and Chung, 2016; Ku and Beck, 2016; Zhou and Peng, 2016; Huang et al., 2016; Dürr and Nayak, 2016; Liu and Kozan, 2016, Yang and Gu, 2016; Singh et al., 2016; Agnetis et al., 2016; Afsar et al., 2016; Jamili, 2016; Wang et al., 2016a; Nouri et al., 2016a; Zhang and Wong, 2016; Zhang and Chiong, 2016; Bürgy and Gröflin, 2016; Koulamas and Panwalkar, 2016; Knopp et al., 2017; Sagawa et al., 2017; Della Croce et al., 2017; Bouazza et al., 2017; Liu et al., 2017; Liu and Kozan, 2017; Chaouch et al., 2017; Grundstein et al., 2017; Yin et al., 2017; Shahrabi et al., 2017; Azzouz et al., 2017; Ferjani et al., 2017, Huang and Yu, 2017; Lu et al., 2017; Luo et al., 2017; Kemmoé-Tchomté et al., 2017; Aschauer et al., 2017; Mokhtari and Hasani, 2017; Piroozfard et al., 2017; Kurdi, 2017; Liu and Chung, 2017; Güçdemir and Selim, 2017; Hamaz et al., 2017; Elmi and Topaloglu, 2017; Upasani et al., 2017; Wu et al., 2017; Plitsos et al., 2017; Ham, 2017; Zandieh et al., 2017; Zhang et al., 2017b; Li et al., 2017; Giglio et al., 2017; Ahmadi-Javid and Hooshangi-Tabrizi, 2017; Beemsterboer et al., 2017, Sreekara Reddy et al., 2017; Zhang et al., 2017a; Courtad et al., 2017; Gerstl et al., 2017; Marzouki et al., 2017; Yazdani et al., 2017; Bozejko et al., 2017; Salido et al., 2017; José Palacios et al., 2017; Pei et al., 2017; El Khoukhi et al., 2017; Kim et al., 2017; Karunakaran et al., 2017; Nouiri et al., 2017; Ahmadov and Helo, 2018; Gondran et al., 2018; Yan et al., 2018; Wu and Sun, 2018; Nagata and Ono, 2018; Fernández Romero et al., 2018; Wang et al., 2018d, Pérez-Rodríguez and Hernández-Aguirre, 2018; Wang et al., 2018a; Arasanipalai Raghavan et al., 2018; Kato et al., 2018; Gong et al., 2018; Rahmati et al., 2018a; Wang et al., 2018c; Sreekara Reddy et al., 2018; Fatih Tasgetiren et al., 2018; Lunardi and Voos, 2018; Burdett and Kozan, 2018; Park et al., 2018; Sharma et al., 2018; Karimi et al., 2018; Iqbal and Al-Ghamdi, 2018; Noroozi et al., 2018; Xie and Chen, 2018; Benttaleb et al., 2018a; Dabah et al., 2018; Robert et al., 2018, Zhang and Wong, 2018; Fu et al., 2018; Güçdemir and Selim, 2018; Defersha and Bayat Movahed, 2018; Tamssaouet et al., 2018; Piroozfard et al., 2018; Tsai et al., 2018; Rahmati et al., 2018b; Heger and Voss, 2018; Wang et al., 2018b; Wu et al., 2018; Aschauer et al., 2018; Marzouki et al., 2018; Shen et al., 2018; Tao and Xu-ping, 2018; Bürgy and Bülbül, 2018; Nouiri et al., 2018; Benttaleb et al., 2018b; Briskorn and Zeise, 2019; Burdett et al., 2019; Hemmati Far et al., 2019; Wang et al., 2019a, Lin et al., 2019b; Al Aqel et al., 2019; Rotondo et al., 2019; Chen and Su, 2019; Zhu et al., 2019; Lange and Werner, 2019; Lu and Wang, 2019; Xiao et al., 2019; Kress et al., 2019; Singhtaun and Nutchaphan, 2019; Qin et al., 2019; Gong et al., 2019a; Xie et al., 2019a; Rooyani and Defersha, 2019; Li et al., 2019b; Wichmann et al., 2019; Wang et al., 2019b; Zhou and Yang, 2019; Lin, 2019; Zheng and Wang, 2019; Zheng and Sui, 2019; Gondran et al., 2019; Gola and Kosowski, 2019; Zhang and Ji, 2019; Cunha et al., 2019, Nayak et al., 2019; Heger and Voβ, 2019; Gong et al., 2019b; Luo et al., 2019; De Araujo and Previero, 2019; Tang et al., 2019; Tamizi and Ghaffari, 2019; Liu et al., 2019; Jamili, 2019; Masmoudi et al., 2019; Denkena et al., 2019; Sun et al., 2019; Zhang et al., 2019; Kress and Müller, 2019; Lin et al., 2019a; Meng et al., 2019; Lu et al., 2019; Dai et al., 2019; Amiri et al., 2019; Li et al., 2019a; Novas, 2019; Tian et al., 2019; Heger and Voss, 2019; Wu and Sun, 2019; Caldeira and Gnanavelbabu, 2019, Samarghandi, 2019; Behmanesh and Zandieh, 2019; Vaez et al., 2019; Coca et al., 2019; Wu et al., 2019; Deng et al., 2019; Buddala and Mahapatra, 2019; Zhang et al., 2020c; Burdett et al., 2020; Lee and Kim, 2020; An et al., 2020; Nogueira et al., 2020; Li et al., 2020a; Shafiee-Gol et al., 2020; Ozolins, 2020a; Xu et al., 2020; Ozturk, 2020; Arnaout, 2020; Chen et al., 2020; Luo et al., 2020c; Wu et al., 2020a; Caldeira et al., 2020; Zhu and Zhou, 2020a; Luo et al., 2020b, Defersha and Rooyani, 2020; Ji et al., 2020; Li et al., 2020c; Mohammadi et al., 2020; Li et al., 2020b; Zhang et al., 2020b; Rocholl et al., 2020; Abderrahim et al., 2020; Gondran et al., 2020; Yepes-Borrero et al., 2020; Ozolins, 2020b; Li et al., 2020d; Barzanji et al., 2020; Demir and Erden, 2020; Aschauer et al., 2020; Ha, 2020; Zhu and Zhou, 2020b; Baykasoğlu et al., 2020; Abdeljaoued et al., 2020; Krim et al., 2020; Zhou et al., 2020; Ding and Gu, 2020, Wang et al., 2020; Ning et al., 2020; Han et al., 2020; Masruroh et al., 2020; Lin et al., 2020; Ambrogio et al., 2020; Zhang et al., 2020a; Vital-Soto et al., 2020; Ebrahimi et al., 2020; Rostami et al., 2020; Zhang et al., 2020d; da Jiang and Wang, 2020; Wu et al., 2020b; wei Li and wen Lu, 2020; Andrade-Pineda et al., 2020; Li and Li, 2020; Soleimani et al., 2020; Pinheiro et al., 2020; Kuo et al., 2020; Zou and Yuan, 2020; da Jiang et al., 2020; Luo et al., 2020a; Soto et al., 2020, Hernández-Gress et al., 2020; Mohammadi and Shirazi, 2020; Oron, 2020; Caricato et al., 2020; Anghinolfi et al., 2021; Wen et al., 2021; Li et al., 2021a; An et al., 2021; Yue and Zhou, 2021; Gupta et al., 2021; Mosheiov et al., 2021; Grosch et al., 2021; Li et al., 2021b; Sun et al., 2021; Kalaki Juybari et al., 2021; Mor et al., 2021; Mor and Mosheiov, 2021; Bıçakcı et al., 2021; Wu and Li, 2021; Wang et al., 2021).

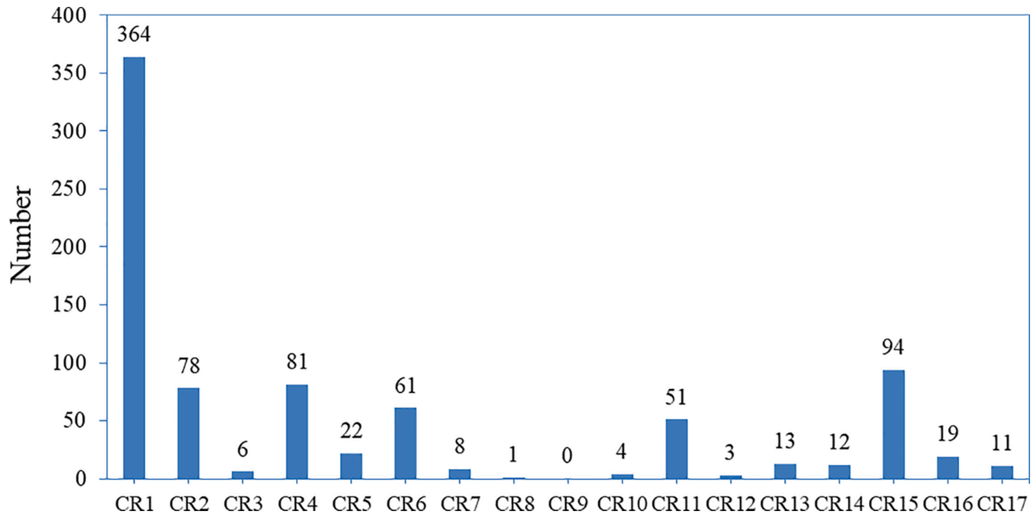

Fig. 4. Number of literature that relate to various elementary criteria.

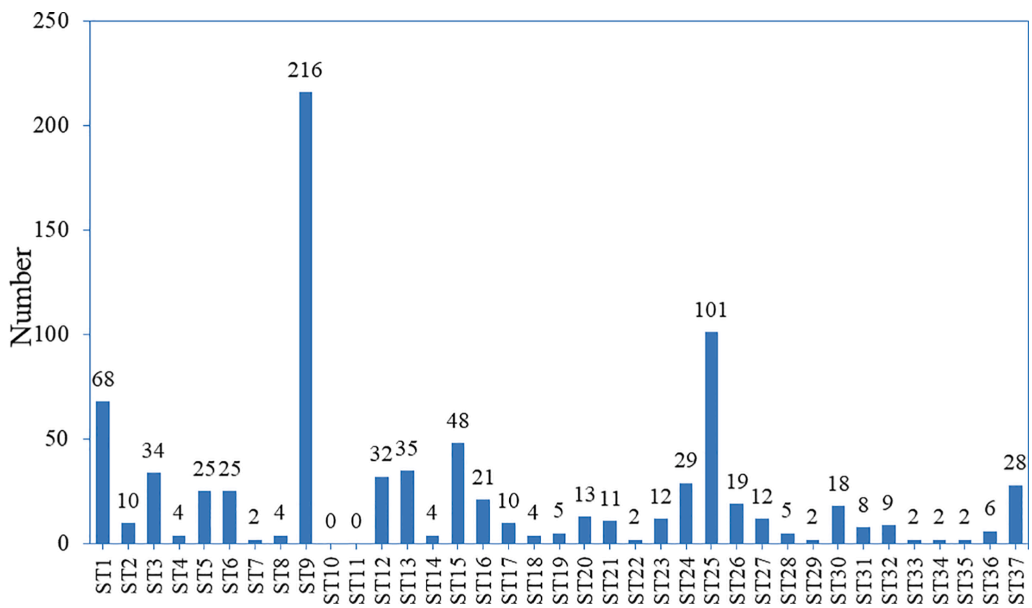

Fig. 5. Number of literature that relate to various basic JSSP models.

and Tamizi and Ghaffari (2019) develop several novel search algorithms to solve JSSP. Kurdi (2017) and Gong et al. (2019a) present improved memetic algorithm for multi-objective JSSP. Asadzadeh (2016) and Scaria et al. (2016) utilize artificial bee colony algorithms to solve JSSP. Cheng et al. (2016b) propose a hybrid evolutionary algorithm for JSSP. After verifying the effectiveness of newly methods, they can be further improved for other complicated models.

(2) It can be seen from Fig. 4 that makespan (i.e., CR1) is the most commonly adopted evaluation criteria. There are approximately 74 % (i.e., 219 out of 297) of the publications are considering CR1 as criterion. Among them, more than 52 % (i.e., 114 out of 219) are single objective problem, i.e., only to minimize makespan. However, real-world scheduling problems are usually multi-objective or many-objective by nature. Hence, it order to get closer to the real scenario, more researches on multi-/many-objective with CR1 should be carried out.

(3) FJSSP is an extension of the JSSP. As mentioned in Section 2, FJSSP can be divided into TFJSSP and PFJSSP, while PFJSSP can be further classified into two categories, i.e., PPFJSSP and CPFJSSP. Actually, we can find that CPFJSSP is a special case of PPFJSSP. From Fig. 5, we can see that PFJSSP is one of the most

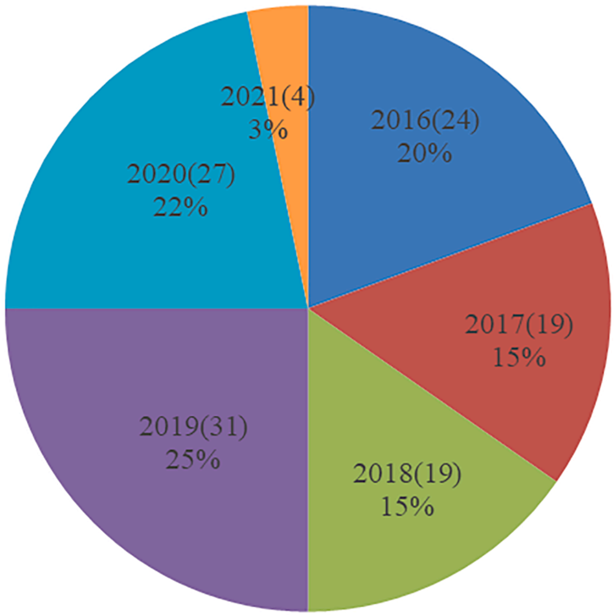

Fig. 6. Distribution of reviewed works on PFJSSP between 2016 to early 2021.

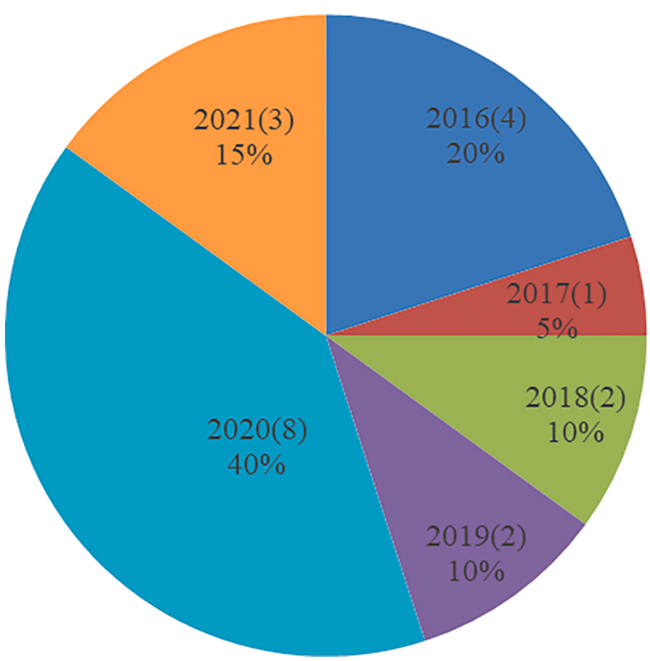

Fig. 7. Distribution of reviewed works on TFJSSP between 2016 to early 2021.

hot research topics in JSSP. More than 41 % (i.e., 124 out of 297) of the publications are related to PFJSSP. The detail distribution of publications on PFJSSP is demonstrated in Fig. 6 by years. We can draw from Fig. 6 that PFJSSP has attracted more and more attention in recent years. This is a reflection of reality that there are so many meaningful practices of the PFJSSP in the real-world scenarios. With continuous development of production environment and the allocation of resources, PFJSSP will be steady to be one of the most hot research direction.

But there are only about 7 % (i.e., 20 out of 297) of all the publications related to TFJSSP. The detailed distribution of publications on TFJSSP is demonstrated in Fig. 7 by years. As can be seen from the figure, there are few studies on TFJSSP compared with PFJSSP, but there is an increasing trend from 2020. This trend can reflects the significance of studying this problem. When considering the due-dates of jobs, FJSSP with alternative routings may have shorter flow time than that of the conventional fixed routings. It can process complicated jobs more efficiently and agile. Besides, it can improve the production performance, such as reducing bottleneck loads, balancing load of the workshop, etc. (Lin and Solberg, 1989). As FJSSP with alternative routings is an effective method to meet due dates, it will attract much attention and interest both from academic and industry in the future.

(4) With the environmental awareness grows, energy and pro-environment considering (i.e., ST25, ST26 and ST27) in JSSP are attracting increasing attentions. From 297 reviewed publications, there are 54 papers (i.e., about 18 %) involving economic, environmental and social impacts. Detail distribution of publications considering energy and pro-environment is illustrated in Fig. 8 by years. Although the total number of publications related to energy and pro-environment is not very large at present, the increasing trend is more and more obvious as can be seen from Fig. 8. From reviewed literature, we can find that the work involving these problems is at the start-up stage, large research work is still required later. Relevant references will be detailed in Section 6.3.
(5) Combining multiple basic subtypes with considering multi-objective is becoming a research trend in JSSP. There are 297 papers reviewed in this work, but the summation of all basic subtype or elementary criteria is 828. There are 43.10 % (i.e., 128 out of 297) involving multiple basic subtypes, and 40.74 % (i.e., 121 out of 297) considering multi-objective respectively. In total, 22.22 % (i.e., 66 out of 297) cover both multiple basic subtypes and multi-objective. More detail description of multi-objective will be reviewed in Section 6.2.
(6) From Table 6, we can see that the reviewed papers almost cover all the basic subtypes of JSSP and elementary criteria. It reflects that all aspects of JSSP play important roles in academic research and industrial application. But it can be concluded from Fig. 5 that most studies still focused on a few subtypes (e.g., ST9, ST25, ST1, ST15, ST12, ST13, etc.). More further research should be conducted for the rest subtypes.
(7) Most criteria of the previous studies considered are time-based and cost-based criteria, which occupy 74 % and 8 % respectively. Distribution of reviewed works classified by type of criterion is illustrated in Fig. 9.

6. Some hot research aspects of JSSP models

In this section, we will present some hot research aspects of JSSP models based on the reviews listed in Table 6. As the models contain so many properties that some representative aspects and development trends are selected below for detailed description.

6.1. Assumption relaxation of JSSP

In the past decades, although various JSSP models have been extensively studied and solved, the aim of scheduling was, in most cases, simply obtaining a feasible solution for the problem (Hopp & Spearman, 1996). Recently, with emergency of new manufacturing technologies (such as Big Data, Artificial Intelligence, Cyber-Physical System, Internet of Things, Smart Sensors, etc.), relaxing assumption and bringing models to practice become possible. More and more studies take real-world environment into consideration now. Some representative references are summarized in Table 7. Column 1 provides the corresponding literature, column 2 to column 19 represent assumption mark AC1, AC2, …, AC21 respectively. As can be seen from Table 7, AC2, AC10, AC11, AC12 and AC13 are seldom reported in the previous literature. The more assumptions relaxed, the more complicated

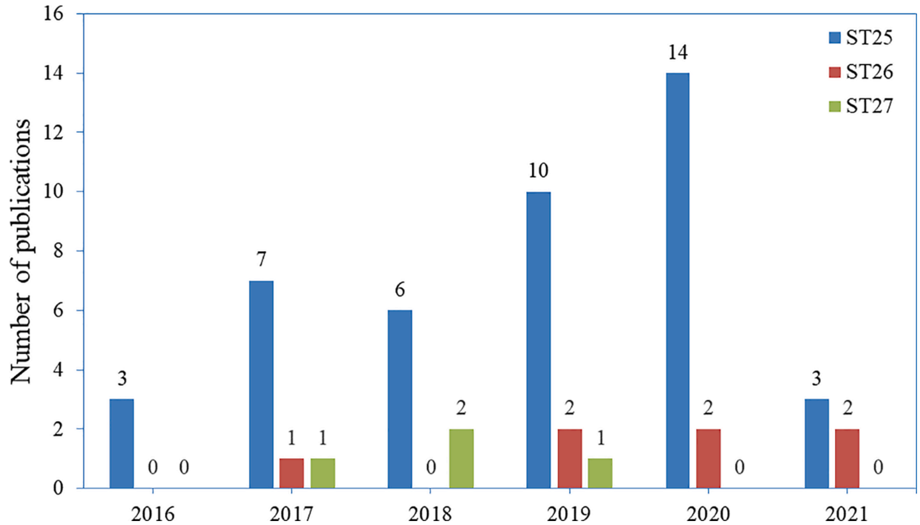

Fig. 8. Distribution of reviewed works considering energy and pro-environment.

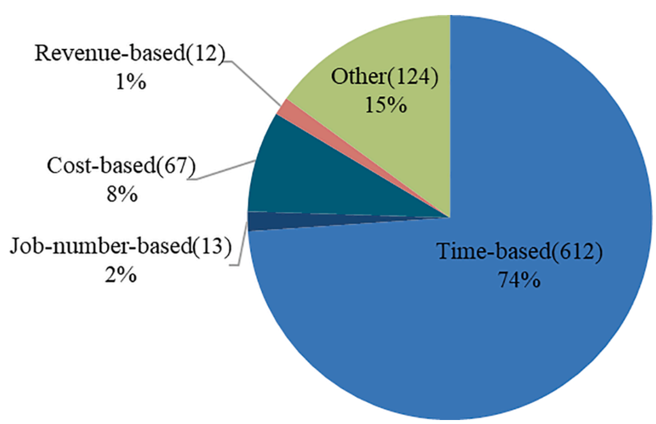

Fig. 9. Distribution of reviewed works classified by type of criterion.

problem is, then the problem is more closer to the real world scenarios.

6.2. Multi-objective optimization of JSSP

In the real-world situations, the JSSP is complicated and NP-hard, it is rare considering only a single-objective function, and often, the practical problem includes several objective functions. Although most JSSPs are studied as a single-objective case recently, but they are mostly multi-objective in nature. As the analysis result showed in Section 5, more and more researches are interested in multi-objective optimization now. Multi-objective optimization (MOP) is concerned to find solutions with optimizing multiple conflicted objectives simultaneously. In general, multi-objective JSSP can be described in mathematical terms as follows (Singh et al., 2016; Huang and Yu, 2017; Lu et al., 2017; Zhu and Zhou, 2020a):

$$minf(X) = min[f_1(X), f_2(X), ..., f_m(X)]$$

$$X = (x_1, x_2, ..., x_n) \in R^n$$

where $f_m(X)$ defines the m-th sub-objective function, X presents a vector of solutions, R^n declares the decision variable space.

Some multi-objective JSSPs with detailed description are summarized in Table 8. In order to facilitate readers to get a general picture of the methods to solve multi-objective JSSP problems, the corresponding algorithms applied in the references are also listed in the table.

In Table 8, the following point needs to be explained additionally: In the literature, the objective of some JSSPs may not list in Table 4, but it can do some equivalent transformations. Take Salido et al. (2016) for example, they propose a methodology of optimizing both makespan and stability objectives. The stability objective is not in Table 4. But it can be equivalently converted to CR2. Because the stability is calculated as an average of the difference between the completion time of the predicted scheduling and the realized completion time.

6.3. Pro-environment and energy-saving related JSSP

In recent years, there has been increased concern on environmental pollution and energy consumption in modern manufacturing industry. Decision makers concern about energy efficiency and environmental sustainability have grown greatly over the last decade (Plitsos et al. 2017). Based on the analysis of Section 5, we can see that the number of studies regarding environmental protection and energy-efficient scheduling is increasing now. The detailed summary of environmental protection and energy consumption consideration references is listed in Table 9. In order to facilitate readers to get a general picture of the methods to solve pro-environment and energy-saving related JSSP problems, the corresponding algorithms applied in the references are also listed in the table. From Table 9, we can find that a very limited number of papers have considered carbon emission in their studies.

6.4. JSSP with distributed manufacturing

With the development of economic globalization, the distributed manufacturing is more and more practical since ‘it allows companies to achieve higher product quality, lower production costs and lower management risks’ (Kahn, 2012). The distributed JSSP (DSJSSP) addresses the allocation of jobs to factories (cells/workshops) geographically distributed and determines a proper operation schedule of each factory/cell simultaneously (Chaouch et al., 2017). It shows much more complicated than classical scheduling ones since two decisions have to be considered. Recently, this problem has become a research trend.

Hsu et al. (2016) formulate DSJSSP as a set of fuzzy constraint satisfaction problems, and present an agent-based fuzzy constraint-directed negotiation mechanism to solve it. Chaouch et al. (2017) use the disjunctive graph to model the problem and apply-three versions of bio-inspired algorithms to solve it with makespan minimization criterion. Xie et al. (2019a) formulate a multi-objective mathematical model of DSJSSP with considering makespan and energy consumption as evaluation criteria. They present an effective multi-objective artificial bee colony algorithm to

Table 7
Summary of JSSP with relaxing typical assumptions from 2016 to early 2021.

Reference	AC																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Li et al. (2016b)				×		×														×	
Ahmadi et al. (2016)						×			×	×								×			
Ning et al. (2016)				×		×				×									×		
Gao and Pan (2016)						×			×								×			×	
Hsu et al. (2016)				×		×															
Li et al. (2016a)											×						×				
Gao et al. (2016b)						×			×												
Tang et al. (2016)						×			×								×				
Gao et al. (2016a)				×		×			×												
Alotaibi et al. (2016)	×			×		×			×									×			
Sobeyko and Mönch (2016)			×	×		×			×												
Kundakcı and Kulak (2016))	×					×												×			
Huang et al. (2016)						×			×												
Knopp et al. (2017)				×					×		×					×	×				
Bouazza et al. (2017)					×	×			×	×							×				
Grundstein et al. (2017)	×			×		×											×	×		×	
Shahrabi et al. (2017)	×																	×			
Azzouz et al. (2017)						×			×								×				
Ferjani et al. (2017)	×					×														×	
Kemmoé-Tchomté et al. (2017)						×			×												
							×														
Wu et al. (2017)						×			×								×				
Plitsos et al. (2017)						×			×								×				
Ham (2017)					×	×			×		×										
Li et al. (2017)									×									×	×		
Zhang et al. (2017a)						×			×							×					
Pei et al. (2017)						×					×						×				
Yan et al. (2018)	×					×						×					×		×		
Arasanipalai Raghavan et al. (2018)			×														×		×		
Gong et al. (2018)						×			×											×	
Park et al. (2018)			×	×															×		
Burdett and Kozan (2018)				×					×												
			×					×													
Güçdemir and Selim (2018))				×		×											×				
Defersha and Bayat Movahed (2018))									×		×						×				
Marzouki et al. (2018)						×			×												
Rahmati et al. (2018a)						×			×									×			
Fernández Romero et al. (2018)									×		×										
Fu et al. (2018)				×													×				
Pérez-Rodríguez and Hernández-Aguirre (2018)						×	×														
Zhang and Wong (2018)						×	×														
Burdett et al. (2019)									×						×						
Lin et al. (2019b)						×			×												
Zhu et al. (2019)				×					×												
Xiao et al. (2019)						×														×	
Qin et al. (2019)						×			×								×				
Zhou and Yang (2019)	×		×	×		×			×												
Heger and Voβ (2019)				×		×			×	×							×				
Gong et al. (2019b)				×					×							×				×	
Kress and Müller (2019)						×			×											×	
Lin et al. (2019a)									×								×	×			
Amiri et al. (2019)	×				×				×												
Novas (2019)									×		×										
Buddala and Mahapatra (2019)						×			×		×										
Zhang et al. (2020c)											×						×				
An et al. (2020)						×			×												
Chen et al. (2020)									×									×			
Caldeira et al. (2020)						×			×										×		
Li et al. (2020b)	×					×			×									×			
Zhang et al. (2020b)									×		×										
Baykasoğlu et al. (2020)						×			×								×	×	×		
Shafiee-Gol et al. (2020)																	×	×			
Demir and Erden (2020)	×			×			×														
Han et al. (2020)						×	×														
Defersha and Rooyani (2020)						×			×		×						×				
An et al. (2021)						×			×												
Li et al. (2021a)									×										×		

Table 8
Summary of multi-objective JSSPs from 2016 to early 2021.

Reference	Codes of Criterion	Objectives	Solving approaches
Li et al. (2016b)	CR1, CR4, CR11, CR13	min(makespan) min(cost)	Branch Population Genetic Algorithm
Fitouri et al. (2016)	CR1, CR6	min(makespan) min(cost)	Shifting rules
Salido et al. (2016)	CR1, CR15	min(makespan) min(energy consumption)	Genetic algorithm
Ahmadi et al. (2016)	CR1, CR2	min(makespan) stability	Non-dominated sorting genetic algorithm (NSGA-II) Non-dominated ranking genetic algorithm (NRGA)
Scaria et al. (2016)	CR1, CR4	min(makespan) min(total tardiness)	Artificial bee colony approach
Kaplanŏglu (2016)	CR1, CR6	min(makespan) min(workload of machines)	Object-oriented approach Simulated annealing algorithm
Gao et al. (2016a)	CR1, CR5	min(makespan) min(mean of earliness and tardiness)	Discrete harmony search
Huang et al. (2016)	CR1, CR6	min(makespan) min(workload of machines)	Particle swarm optimization
Yang and Gu (2016)	CR1, CR4	min(makespan) min(total tardiness)	Non-order strategy Local search
Zhang and Chiong (2016)	CR4, CR15	min(total tardiness) min(energy consumption)	Multi-objective genetic algorithm incorporated with local search
Bouazza et al. (2017)	CR1, CR2	min(makespan) min(total completion time)	Reinforcement Q-learning algorithm
Liu et al. (2017)	CR1, CR16	min(makespan) min(carbon emission)	Hybrid Fruit fly optimization algorithm (HFOA)
Grundstein et al. (2017)	CR1, CR2, CR10, CR6	min(makespan) min(total completion time) min(work in process) max(machine utilization)	Autonomous production control method (APC)
Yin et al. (2017)	CR1, CR15, CR17	min(makespan) min(energy consumption) min(noise emission)	Multi-objective genetic algorithm (MOGA)
Huang and Yu (2017)	CR1, CR4, CR11	min(makespan) min(total tardiness) min(lot-splitting cost)	Multi-pheromone ant colony optimization (MACO)
Lu et al. (2017)	CR1, CR15	min(makespan) min(total additional resource consumption)	Multi-objective discrete virus optimization algorithm (MODVOA)
Mokhtari and Hasani (2017)	CR1, CR15, CR6	min(total completion time) min(energy consumption) max(total availability of the system)	Hybrid genetic algorithm with simulated annealing algorithm
Kurdi (2017)	CR1, CR3, CR4	min(makespan) min(total weighted earliness) min(total weighed tardiness)	Improved island model memetic algorithm with a cooperation phase (IIMMA)
Plitsos et al. (2017)	CR1, CR2, CR6, CR15	min(makespan) min(total flow time) min(total idle time) min(energy consumption)	Iterated local search
Zhang et al. (2017b)	CR1, CR6, CR15	min(makespan) max(machine utilization) min(energy consumption)	A two-layer scheduling method
Giglio et al. (2017)	CR11, CR15	min(processing cost) min(energy consumption)	Relax-and-fix heuristic
Zhang et al. (2017a)	CR1, CR6, CR15	min(makespan) min(total idle time) min(energy consumption)	Gene Expression Programming algorithm
Salido et al. (2017)	CR1, CR15	min(makespan) min(energy consumption)	Memetic algorithm Local search
Nouiri et al. (2017)	CR1, CR2	min(makespan) min(completion time)	Two-stage particle swarm optimization (2S-PSO)
Wu and Sun (2018)	CR1, CR15	min(makespan) min(energy consumption)	Non-dominated sorting genetic algorithm II (NSGA-II)
Kato et al. (2018)	CR1, CR6	min(makespan) max(machine utilization)	Particle swarm optimization + Random restart hill climbing (PSO + RRHC)
Gong et al. (2018)	CR1, CR11, CR15	min(makespan) min(total worker cost) min(energy consumption)	Newly proposed hybrid genetic algorithm (NHGA)
Wang et al. (2018c)	CR11, CR15	min(production cost) min(energy consumption)	Genetic algorithm Particle swarm optimization
Sreekara Reddy et al. (2018)	CR1, CR6	min(makespan) max(machine utilization)	Multi-objective teacher learning-based optimization algorithm (MOTLBO)
Karimi et al. (2018)	CR2, CR6	min(completion time) max(machine utilization)	Non-dominated sorting cuckoo search (NSCS) Multi-objective teaching–learning-based optimization (MOTLBO)
Robert et al. (2018)	CR1, CR6	min(makespan) max(machine utilization)	Multi-objective heuristic Kalman algorithm (MOHKA)

(continued on next page)

Table 8 (*continued*)

Reference	Codes of Criterion	Objectives	Solving approaches
Güçdemir and Selim (2018)	CR1, CR2, CR4	min(makespan) min(flow time) min(total tardiness)	Simulation modelling and multi-criteria decision making
Piroozfard et al. (2018)	CR4, CR16	min(total tardiness) min(carbon footprint)	Multi-objective genetic algorithm (MOGA)
Rahmati et al. (2018b)	CR1, CR11, CR6	min(makespan) min(total maintenance cost) max(system reliability)	Multi-objective biogeography based optimization (MOBBO) algorithm Pareto envelope-based selection algorithm (PESA) New version of non-dominated sorting genetic algorithm (NSGAIII) Multi-objective evolutionary algorithm based on decomposition (MOEAD)
Nouiri et al. (2018)	CR1, CR15	min(makespan) min(energy consumption)	Particle swarm optimization
Rotondo et al. (2019)	CR1, CR4, CR6	min(makespan) min(job's lateness) min(resource's idle time)	Heuristics
Qin et al. (2019)	CR1, CR4, CR11	min(makespan) min(total delivery delay time) min(total production cost)	Multi-objective grey wolf optimizer (HDMGWO) Improved tabu search (ITS)
Gong et al. (2019a)	CR1, CR4	min(makespan) min(total tardiness)	An effective memetic algorithm (EMA)
Li et al. (2019b)	CR1, CR11	min(makespan) min(total setup costs)	Elitist nondominated sorting hybrid algorithm (ENSHA)
Xie et al. (2019a)	CR1, CR15	min(makespan) min(energy consumption)	Multi-objective artificial bee colony algorithm (MOABC)
Zhou and Yang (2019)	CR2, CR4	min(mean flow time) min(mean weighted tardiness) min(maximum tardiness)	Multi-objective genetic programming based hyper-heuristic methods (MO-GPHH)
Zheng and Wang (2019)	CR1, CR11	min(makespan) min(processing cost)	Epsilon-constraint method
Zheng and Sui (2019)	CR1, CR11	min(makespan) min(cost of selected processing routes)	Non-dominated sorting genetic algorithm II (NSGA-II)
Gong et al. (2019b)	CR1, CR6, CR11, CR15	min(makespan) min(energy cost + labor cost) min(maximal machine workload) min(total machine workload)	Non-dominated sorting genetic algorithm III (NSGA-III)
Luo et al. (2019)	CR1, CR15	min(makespan) min(energy consumption)	Multi-objective grey wolf optimization (MOGWO)
Liu et al. (2019)	CR1, CR15	min(makespan) min(energy consumption)	Genetic algorithm-glowworm swarm optimization-green transport heuristic strategy (GA-GSO-GTHS)
Dai et al. (2019)	CR1, CR15	min(makespan) min(energy consumption)	Enhanced genetic algorithm (EGA)
Amiri et al. (2019)	CR1, CR2, CR7	min(makespan) min(total flow time) min(total weighted flow time) min(number of late jobs)	Simulation optimization approach
Behmanesh and Zandieh (2019)	CR1, CR9	min(makespan) min(number of unscheduled surgical cases)	Multi-objective two-level ant colony optimization
Wu et al. (2019)	CR1, CR15	min(makespan) min(energy consumption)	Multi-objective hybrid pigeon-inspired optimization and simulated annealing (MOHPIOSA)
An et al. (2020)	CR1, CR11, CR14, CR15	min(makespan) min(total production cost) min(total tardiness) min(total energy consumption)	Multi-objective evolutionary algorithm with Pareto elite storage strategy (HMOEA/P)
Caldeira et al. (2020)	CR1, CR15	min(makespan) min(energy consumption)	Backtracking search algorithm (BSA)
Zhu and Zhou (2020a)	CR1, CR6	min(makespan) min(total workload of all machines) min(maximum machine workload)	Evolutionary multi-objective grey wolf optimizer (EMOGWO)
Li et al. (2020b)	CR1, CR15	min(makespan) min(energy consumption)	Non-dominated sorting genetic algorithm II (NSGA-II)
Li et al. (2020c)	CR1, CR6, CR16	min(makespan) min(machine loading) min(total carbon emission)	Improved artificial bee colony algorithm (IABC)
Gondran et al. (2020)	CR1, CR15	min(makespan) min(power threshold)	Non-dominated sorting genetic algorithm II (NSGA-II) Iterated greedy randomized adaptive search procedure coupled with an evolutionary local search (iGRASP×ELS)
Yepes-Borrero et al. (2020)	CR1, CR11	min(makespan) min(number of resources)	Iterated Pareto greedy algorithm
Baykasoğlu et al. (2020)	CR1, CR2, CR4	min(makespan) min(mean flow time) min(schedule instability) min(mean tardiness)	Greedy randomized adaptive search procedure (GRASP)
Wang et al. (2020)	CR1, CR6, CR15	min(makespan) min(total workload of machines) min(energy consumption)	Infinitely repeated game optimization method

(*continued on next page*)

Table 8 (*continued*)

Reference	Codes of Criterion	Objectives	Solving approaches
Ning et al. (2020)	CR1, CR11, CR15, CR16	min(makespan) min(total cost) min(penalty) min(energy consumption) min(total carbon emission)	Improved quantum bacterial optimization algorithm (IQBFO)
Zhang et al. (2020a)	CR1, CR2	min(makespan) min(total completion time)	Improved LS-based algorithm (ILS)
Ebrahimi et al. (2020)	CR4, CR11, CR15	min(energy cost) min(tardiness penalty)	Hybrid ant colony optimization and simulated annealing (ACO-SA)
Zhang et al. (2020d)	CR1, CR4, CR6	min(makespan) min(total tardiness) min(total workload)	Distributed ant colony optimization
Jiang and Wang (2020)	CR1, CR11	min(makespan) min(total electricity cost)	Hybrid multi-objective evolutionary algorithm based on decomposition (HMOEA/D)
Jiang et al. (2020)	CR1, CR15	min(makespan) min(energy consumption)	Modified multi-objective evolutionary algorithm with decomposition (MMOEA/D)
Luo et al. (2020a)	CR4, CR11, CR15	min(total tardiness) min(togal energy cost) min(delay caused by the schedule changes)	Event-driven policy Genetic algorithm
Soto et al. (2020)	CR1, CR6	min(makespan) min(max workload) min(total workload)	Non-dominated sorting genetic algorithm II (NSGA-II) Multi-objective parallel branch-and-bound algorithm (MBB)
Anghinolfi et al. (2021)	CR1, CR15	min(makespan) min(energy consumption)	Split-greedy heuristic (SGH) Exchange search (ES)
Wen et al. (2021)	CR1, CR4, CR16	min(makespan) min(total tardiness) min(total carbon emission)	Non-dominated sorting genetic algorithm II (NSGA-II) N5 neighborhood structure
Grosch et al. (2021)	CR1, CR11, CR15	min(makespan) min(energy related cost)	Non-dominated sorting genetic algorithm II (NSGA-II)
An et al. (2021)	CR1, CR2, CR4, CR6	min(makespan) min(mean flow time) min(total delay time) min(critical machine workload) min(total workload) min(total production cost)	Improved non-dominated sorting biogeography-based optimization (INSBBO)
Li et al. (2021b)	CR2, CR11	min(cycle time) min(total cost)	Multi-objective migrating bird optimization (MMBO)
Mor et al. (2021)	CR1, CR2	min(makespan) min(total completion time) min(total weighted completion time)	Pseudo-polynomial dynamic programming algorithm

evaluate these two objectives. Jiang et al. (2020) is the first research work to solve the energy-efficient DSJSSP minimizing both makespan and total energy consumption simultaneously through multi-objective evolutionary algorithm. Combining DSJSSP with the flexible attribute is also a research trend. Tang et al. (2016) address a flexible multi-cell part scheduling problem where parts may need to visit machines in different cells. An integer nonlinear programming model is formulated and an auction-bid approach is designed to solve it. When to solve the problem of FJSSP with considering distributed manufacturing cells, Wu et al. (2017) develop a genetic algorithm and compare the effects between different chromosome representations. In order to minimize the maximum completion time, Marzouki et al. (2018) propose an algorithm named "Chemical Reaction Optimization" to solve DSFJSSP. Furthermore, some other extend models of DSFJSSP are also reported in the literature. Lin et al. (2019a) address a DSFJSSP involving preventive maintenance. They propose a genetic algorithm with considering incomplete chromosome representations and shadow chromosomes to solve the problem. Luo et al. (2020b) propose an extended model of DSFJSSP with transfers. A mathematical model is constructed with the optimization objectives, including makespan, maximum workload of the factories, and the total energy consumption. Lin et al. (2020) present a problem involving the joint decision of process planning and scheduling in the context of DSFJSSP and develop a genetic algorithm to solve it. As mentioned in the literature review, we can find that the makespan and evolutionary algorithms are most used objective and solving approaches respectively in DSJSSP.

6.5. JSSP with considering robot/AGV

Robots and AGVs are widely used in the real-life manufacturing systems to improve productivity, reduce cost and achieve better quality (Li et al., 2020d). In order to solve a JSSP with considering transportation times and many robots, Nouri et al. (2016a), Nouri et al. (2016b) develop two new metaheuristic hybridization approaches. Afsar et al. (2016) propose a master/slave approach to solve JSSP with transportation constraints, where transport operation is conducted by a fleet of homogenous vehicles. Liu and Kozan (2017) introduce a new scheduling problem called Blocking JSSP with Robotic Transportation (BJSSRT). They propose an innovative algorithm to construct initial solution, and embedded with some metaheuristic algorithms to find the near-optimal solution. In a study conducted by Yan et al. (2018), they address a real-time scheduling problem in a robotic cell. Karimi et al. (2018) investigate a job-shop type that uses AGVs to transfer materials between the shops. To generate the optimal schedule for AGVs in a reentrant blocking job shop environment, Heger and Voss (2018) present a mixed integer linear programming formulation. Gola and Kosowski (2019) develop a unique approach to the problem of material handling control with respect to AGV path routing. Abderrahim et al. (2020) develop a variable neighborhood search algorithm to address a JSSP in vehicle based manufacturing facility. Besides, some other JSSP subtypes are also taken into account for integration. Heger and Voβ (2019) combine FJSSP with considering travel times of AGVs, and propose a dispatching approach to solve it. Mohammadi and Shirazi

Table 9
Summary of JSSP involving environment- and energy-aware from 2016 to early 2021.

Reference	Energy consumption	Carbon footprint	Other indicators	Solving approaches
Fitouri et al. (2016)	√			Shifting rules
Alotaibi et al. (2016)	√			Multi-agent system (MAS)
Zhang and Chiong (2016)	√			Multi-objective genetic algorithm incorporated with local search
Liu et al. (2017)		√		Hybrid Fruit fly optimization algorithm (HFOA)
Yin et al. (2017)	√		noise emission	Multi-objective genetic algorithm (MOGA)
Lu et al. (2017)	√			Multi-objective discrete virus optimization algorithm (MODVOA)
Mokhtari and Hasani (2017)	√			Hybrid genetic algorithm with simulated annealing algorithm
Plitsos et al. (2017)	√			Iterated local search
Zhang et al. (2017b)	√			A two-layer scheduling method
Giglio et al. (2017)	√			Relax-and-fix heuristic
Zhang et al. (2017a)	√			Gene Expression Programming algorithm
Salido et al. (2017)	√			Memetic algorithm Local search
Wu and Sun (2018)	√			Non-dominated sorting genetic algorithm II (NSGA-II)
Gong et al. (2018)	√		noise emission	Newly proposed hybrid genetic algorithm (NHGA)
Wang et al. (2018c)	√			Genetic algorithm
Iqbal and Al-Ghamdi (2018)	√			Simulated annealing algortithm
Piroozfard et al. (2018)		√		Multi-objective genetic algorithm (MOGA)
Nouiri et al. (2018)	√			Particle swarm optimization
Xie et al. (2019a)	√			Multi-objective artificial bee colony algorithm (MOABC)
Zhang and Ji (2019)		√		Digital twin-driven method
Gong et al. (2019b)	√			Non-dominated sorting genetic algorithm III (NSGA-III)
Luo et al. (2019)	√			Multi-objective grey wolf optimization (MOGWO)
Zhang et al. (2019)	√			Gene expression programming-based rule mining algorithm (GEP-RM)
Masmoudi et al. (2019)	√			Heuristic
Liu et al. (2019)	√			Genetic algorithm-glowworm swarm optimization-green transport heuristic strategy (GA-GSO-GTHS)
Meng et al. (2019)	√			Simulation (CPLEX)
Dai et al. (2019)	√			Enhanced genetic algorithm (EGA)
Wu et al. (2019)	√			Multi-objective hybrid pigeon-inspired optimization and simulated annealing (MOHPIOSA)
An et al. (2020)	√			Multi-objective evolutionary algorithm with Pareto elite storage strategy (HMOEA/P)
Caldeira et al. (2020)	√			Backtracking search algorithm (BSA)
Li et al. (2020c)		√		Improved artificial bee colony algorithm (IABC)
Li et al. (2020b)	√			Non-dominated sorting genetic algorithm II (NSGA-II)
Gondran et al. (2020)	√			Non-dominated sorting genetic algorithm II (NSGA-II) Iterated greedy randomized adaptive search procedure coupled with an evolutionary local search (iGRASP×ELS)
Wang et al. (2020)	√			Infinitely repeated game optimization method
Ning et al. (2020)	√	√		Improved quantum bacterial optimization algorithm (IQBFO)
Ambrogio et al. (2020)	√			–
Ebrahimi et al. (2020)	√			Hybrid ant colony optimization and simulated annealing (ACO-SA)
Jiang et al. (2020)	√			Modified multi-objective evolutionary algorithm with decomposition (MMOEA/D)
Luo et al. (2020a)	√			Event-driven policy Genetic algorithm
Zhou et al. (2020)	√			Hybrid multi-objective opposite-based learning evolutionary algorithm (HMOLEA)
Soleimani et al. (2020)	√			Genetic algorithm (GA) Cat swarm optimization (CSO) Interactive artificial bee colony (IABC)
Anghinolfi et al. (2021)	√			Split-greedy heuristic (SGH) Exchange search (ES)
Wen et al. (2021)		√		Non-dominated sorting genetic algorithm II (NSGA-II) N5 neighborhood structure
Grosch et al. (2021)	√			Non-dominated sorting genetic algorithm II (NSGA-II)

(2020) formulate a simulation-based model involving classical routing strategies with routing flexibility. Sun et al. (2021) formulate a novel robotic JSSP model with considering deadlock and robot movement. The multi-objective function is widely reported in JSSP with considering robot/AGV. Dai et al. (2019) formulate a multi-objective optimization model for a flexible job shop with transportation constraints. Li et al. (2021b) develop a multi-objective mixed-integer programming model with collaborative robots to optimize the cycle time and the purchasing cost simultaneously.

With continues development of automation, more and more robots and AGVs will be extensively used. We think that scheduling involving robots and AGVs will become a hot research topic in the future.

7. Conclusion and directions for future research

In this paper a systematic survey of JSSP types and models are presented. Starting with an introduction to JSSPs, some previous review papers are presented and classified. Next, the entities and their attributes, common basic subtypes, measures of performance, and some detailed classifications of JSSP are summarized based on the researches from mid-1960s to 2020s, and, the general representation and overview of JSSP models are provided. Then, about 300 published papers in 72 journals ranging from 2016 to early 2021 are discussed and analyzed. Finally, some hot research aspects of JSSP models are depicted in detail.

Based on the discussions and analysis on the types and models of JSSP, some notable findings are listed as follows.

(1) Classical JSSP model is useful in understanding the scheduling problem and helpful for verifying the effectiveness of the new algorithm and approach. So when we developing novel methods for JSSP, classical JSSP model can be tested firstly, then extend to other complicated models.
(2) Most previous studies focused on PFJSSP as there are so many meaningful practices in the reality. But a very little attention has been paid on TFJSSP, although FJSSP with alternative routings is an effective method to meet due dates.
(3) Nowadays, JSSP related to economic, environmental and social impacts is investigated by increasing numbers of researchers. Although, the total number of publications on this issue is seldom reported now, the growth trend of interest is obvious.
(4) The majority of previous studies adopted makespan as evaluation criterion. Among these studies, more than half of them take minimizing the makespan into account as a single objective.
(5) Time-based is the most criterion that the previous studies have been considered. Other types of criterion are seldom reported.
(6) JSSP is a thriving area of scheduling research, the reviewed papers almost cover all the basic subtypes and elementary criteria. And combining multiple subtypes with considering multi-objective is becoming a research trend.

Based on the above analysis, we can draw some suggestions for future research on types and models of JSSP.

(1) FJSSP is an approach to process complicated jobs more efficiently and agile. So that more attentions need to be paid on this issue.
(2) Future research can be focus on the cost-based and revenue-based criteria which are few presented in the previous literature.
(3) As real-world scenarios are usually multi-/many-objective by nature, more researches involving multiple objectives should be carried out, instead of just thinking about the only.
(4) Only about 18 % papers involving environment and energy are reported, it is very limited compared with other research topic. We think environment- and energy-aware JSSP is a very meaningful research perspective.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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