Applied Soft Computing Journal 198 (2026) 115269

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Meta-heuristic algorithms for optimization of hybrid flowshop scheduling problems: A comprehensive review of the state of the art

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HIGHLIGHTS

- 328 articles published in a decade from 2015 to 2024 are determined as a result of the execution of the phases of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology and analyzed.
- PRISMA methodology enables researchers to realize systematic reviews for presentation of a full overview related to the research area and meta-analyses for demonstration of the mathematical results by applying four phases as identification, screening, eligibility, and included.
- The evolutionary and swarm-based algorithms are the most utilized meta-heuristics to solve hybrid flowshop scheduling problems (HFSPs) when an assessment is made in terms of the inspiration source of meta-heuristic algorithms.
- Various performance metrics are utilized to assess the performance of the proposed meta-heuristics for solving both single-objective and multi-objective HFSPs.
- An analysis has been performed related to parameter tuning methods due to the importance of determination of the most suitable parameter levels on the solution quality obtained from the meta-heuristics.
- The utilization of new generation meta-heuristics for solving HFSPs and comparing their performance with existing and the most utilized algorithms can be proposed as a future research suggestion.
- It has been aimed to demonstrate the recent advances and research gaps in this research area by answering 12 predetermined research questions and to present a beneficial road map for different stakeholders such as academic researchers, experts, and industrial managers.

ARTICLE INFO

Keywords:
Hybrid flowshop scheduling
Meta-heuristic algorithms
PRISMA
Literature review
Optimization

ABSTRACT

The hybrid flowshop scheduling problem (HFSP), which combines classical flowshop and parallel machine scheduling environments, has gained significant attention in recent years and has various application areas such as manufacturing, healthcare management, seaport operations, agricultural activities, and cloud computing. The HFSP considers multiple stages, at least one of them includes identical, uniform, or unrelated parallel machines, and aims to determine machine assignments and job sequences simultaneously at each stage. Since the HFSP has an NP-hard structure as a combinatorial optimization problem, exact methods like the branch & bound algorithm are not capable of obtaining promising solutions for large-sized problems within a reasonable time. At this point, meta-heuristic algorithms inspired by nature and based on mathematical concepts are effectively utilized to solve this type of complicated optimization problem. Therefore, in this paper, a state-of-the-art review on meta-heuristics applied to solve HFSPs has been carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, which enables the realization of systematic reviews and meta-analyses in a specified research domain. As a result of the execution of this systematic review methodology, 328 articles published in a decade from 2015 to 2024 have been determined and these articles have been statistically and mathematically analyzed in terms of various characteristics such as year, country, journal, publisher, objective functions, meta-heuristic optimization methods, performance metrics, test instances, and parameter optimization techniques. The analysis results have been presented through charts and tables for visual demonstration with the aim of revealing the current state of the existing literature, recent developments, and future research suggestions related to meta-heuristic algorithms used to solve the HFSPs. Thus, it has been desired to provide a beneficial road map for researchers conducting research in this area.

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https://doi.org/10.1016/j.asoc.2026.115269
Received 21 June 2025; Received in revised form 16 March 2026; Accepted 17 April 2026
Available online 20 April 2026

1. Introduction

The hybrid flowshop scheduling problem (HFSP), in which a set of jobs is processed in several stages that at least one of them has identical, uniform, or unrelated parallel machines, is an integration of classical flowshop and parallel machine scheduling environments [1]. Although this integration increases the complexity of the addressed problem, it provides to increase the throughput and capacity of the flowshop, to improve productivity, and to balance the machine load [2]. In hybrid flowshops, also known as flexible and multiprocessor flowshops in the literature, it is aimed to make two decisions for the minimization of a specific objective function as assigning the jobs to a machine at each stage and sequencing these jobs in the parallel machines in which they are assigned [1,3]. The extended versions obtained by adding practical constraints such as sequence-dependent setup times, limited buffer, machine eligibility, and precedence constraints among jobs to the basic HFSP have meaningfully increased the possible range of the application of the HFSP in practice. Furthermore, the HFSP has gained special attention in recent years since this problem is able to capture a wide range of real-life production environments [4]. In this context, it is possible to say that the most common application area of the HFSP is manufacturing in different industries such as steel [5], electronic [6], automotive [7], glass [8], furniture [9], construction [10], food [11], paper [12], petrochemical [13], and textile [14]. On the other hand, there are various application areas of this scheduling problem like container terminal operations [15,16], transportation [17], supply chain management [18], underground mining [19], operating room scheduling [20,21], cloud computing [22], sugarcane cultivation [23], tree data gathering [24], aviation ordnance handling [25], and pharmacy automation dispensing systems [26] except manufacturing.

It was proven by [27] that the two-stage HFSP, in which there are identical parallel machines at least one of the stages, is a type of combinatorial optimization problem that is it has an NP-hard characteristic. Due to the NP-hardness of the HFSP, it is not possible to obtain remarkable solutions for medium and large-sized problems in a reasonable time through exact methods such as the branch and bound algorithm [28]. Therefore, heuristic and meta-heuristic algorithms are proposed for solving this type of scheduling problem as the problem size increases from small to large. While heuristics are problem-dependent, meta-heuristic algorithms include general mechanisms that enable them to cope with almost all optimization problems [29]. Meta-heuristics inspired by natural phenomena such as genetic, swarm behavior, and evolution are effectively utilized as stochastic-based algorithms for solving complex optimization problems in various fields such as engineering, finance, and computer science. These algorithms are preferred since they provide to find near-optimal solutions in a reasonable time for large-sized problems, although they do not guarantee obtaining the optimal solution because of their random nature [30]. The term "meta-heuristic", which was first introduced by Glover in 1986, consists of a combination of the words meta and heuristic. The word "meta" is a Greek suffix whose meaning is 'beyond, in an upper level' and indicates higher-level heuristics in contrast to problem-specific heuristics [31,32].

The success of meta-heuristics in solving a given optimization problem depends on providing a balance between exploration (diversification) and exploitation (intensification) phases [31]. It is aimed to discover the promising areas of the search landscape in the exploration phase. A rough prediction of the global optimum related to the handled problem is obtained in this phase. It is required to realize a search in a promising region in order to obtain the best solution in the exploitation phase. In other words, the search is realized locally around the promising areas obtained in the exploration phase, and it may not be possible to find an optimum solution without this capability [32,33]. Premature convergence is a concept that states the whole population converges to local optima in early iterations. This state generally reveals when the algorithm cannot escape from local optimum due to an imbalance between exploration and exploitation [32].

Meta-heuristic algorithms can be classified into two groups as individual-based and population-based. The algorithm works with the principle of evaluating and improving an initial solution until the termination condition is satisfied in individual-based algorithms. Although these algorithms are advantageous in terms of the number of iterations and computational effort, they suffer from premature convergence [33]. Simulated Annealing, Tabu Search, Greedy Randomized Adaptive Search Procedure, Variable Neighborhood Search, and Iterated Local Search can be given as examples of them [31].

On the other hand, a set of candidate solutions is utilized to obtain the global optimum in population-based algorithms. These algorithms are more advantageous due to high exploration of the search space and lower probability of early convergence. Population-based algorithms can be divided into two main groups as evolutionary and swarm-based algorithms. Evolutionary concepts in nature are imitated to solve optimization problems in evolutionary algorithms. Crossover and mutation are the main operators in these algorithms. Mutation is the main mechanism of the exploration phase and contributes to global search by changing some of the solutions significantly. Besides, crossover is the main operator of the exploitation phase and performs local search around the promising solutions to find the global optimum. A position vector is generally defined for each solution and moves it through a set of rules in swarm-based algorithms [33]. While Genetic Algorithm, Estimation of Distribution Algorithm, and Differential Evolution can be given as examples for evolutionary algorithms, Ant Colony Optimization, Particle Swarm Optimization, and Artificial Bee Colony are examples of swarm-based algorithms [31].

When the existing literature is examined in detail, it is seen that there are many review papers related to meta-heuristics utilized for different problems such as vehicle routing problem [34], grouping problems [35], multiple sequence alignment [36], feature selection [37], renewable-powered smart grid optimization [38], revolutionizing sustainable supply chain management [39], circular supply chain intelligent systems [40], power systems problems [41], TSP-based scheduling optimization problem [42], complex optimization problems [43], electric power systems optimization [44], bilevel optimization [45], building energy optimization [46], real-world electrical and civil engineering application [47], and autonomous path planning and unmanned aerial vehicles [48]. On the other hand, because of the complexity of the HFSP rooted from NP-hardness and crucial scientific interest for this problem, there are several review studies related to HFSPs published in recent years in the literature. Hwang and Lin [49] presented a survey of more than 37 studies related to manufacturing models developed for two-stage flexible flowshops with dedicated machines and presented future research suggestions by analyzing these papers in terms of solution methodology and complexity. Lee and Loong [50] classified the papers relevant to the HFSP for the 2000–2016 year interval according to machine environment, system constraints, objective functions, and solving methods. Tosun et al. [51] analyzed 219 articles based on the HFSP from the year 2010 to the year 2019 in terms of solution techniques by classifying them into exact solution, heuristic, and meta-heuristic. Besides, they realized detailed analyses based on meta-heuristic algorithms. Neufeld et al. [4] examined a total of 130 articles related to multi-objective HFSP published between 2008 and 2021. They aimed to contribute to the literature by providing a comprehensive review related to this topic. Utama et al. [52] reviewed 90 articles from January 2008 to December 2022 and aimed to present a systematic review based on energy-efficient HFSP. They classified the examined articles in terms of year, country, journal, publisher, objective function, and optimization procedure. As a result of the investigation of the review papers related to the meta-heuristic optimization algorithms and the HFSP separately, it is seen that there is no review study that deeply focuses on meta-heuristics applied for solving HFSPs. Therefore, we aimed to reveal a comprehensive review of the state of the art that also includes classification of the meta-heuristics according to the inspiration source and the number of solutions, presentation of performance metrics and test instances used for performance evaluation of the meta-heuristic algorithms, and assessment of the parameter tuning methods utilized for determination of the most suitable parameter values as different from the existing survey papers in the literature.

In this study, a comprehensive and systematic literature review for the decade from 2015 to 2024 has been realized using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) methodology for meta-heuristic algorithms utilized for solving HFSPs. PRISMA methodology includes four phases as identification, screening, eligibility, and included. In the scope of this study, it has been aimed to realize a more focused and systematic review study by following these phases, respectively. Various academic databases have been searched via different keywords, and 3786 records have been obtained in the identification phase. After duplicated records have been removed, 2195 records have been examined, and 328 articles have been determined for meta-analyses by utilizing exclusion criteria in the screening and eligibility phases. 328 included articles have been statistically and mathematically analyzed according to various characteristics such as year, country, journal, publisher, objectives, meta-heuristic algorithms, performance metrics, test instances, and parameter optimization methods. Thus, it has been aimed to present a beneficial road map to researchers studying on this scheduling problem and reveal recent developments related to meta-heuristics utilized for solving HFSPs.

The rest of this paper has been organized as follows. In Section 2, the HFSP has been introduced in detail in terms of machine environment, constraints and processing characteristics, and objective functions. In Section 3, the steps of the review methodology have been explained, and a summary classification related to 328 included articles has been presented. The statistical analysis of review results has been realized according to some features, such as year, country, journal, publisher, objective functions, meta-heuristic algorithms, performance metrics, test instances, and parameter optimization methods in Section 4. The study has been concluded by giving conclusions and future research directions in Section 5.

2. Hybrid flowshop scheduling problem

Scheduling is a decision-making process that is utilized in many manufacturing and service industries, and it is concerned with the allocation of resources to tasks to optimize one or more objectives [53]. Single machine, parallel machine, flowshop, job shop, and open shop are different scheduling environments commonly handled with various constraints and objective functions in the literature [1]. The flowshop scheduling problem was introduced with Johnson's pioneer article in 1954, and a set of jobs is processed in a series of stages, respectively, in which each stage has a single machine in the classical flowshop scheduling problem. The HFSP, in which the flowchart related to it is given in Fig. 1, can be defined as the integration of two classical scheduling environments as parallel machine and flowshop [54]. It is aimed to determine the job sequence and machine assignment for each stage in the HFSP [55]. The characteristics related to standard form of it have been given as follows [56].

(i) All jobs and machines are available at time zero.
(ii) Parallel machines are identical at any stage.
(iii) Any machine can process only one job and any job can be processed by only one machine at a given time period.
(iv) The setup times are negligible.
(v) Preemption is not allowed.
(vi) There is unlimited buffer between two consecutive stages.
(vii) The data is deterministic and known in advance.

The HFSPs can be classified through a α / β / γ triplet proposed by [57] according to machine environment (α), constraints and processing characteristics (β), and objective functions (γ). In this triplet, parameter α defines the shop structure, indicating the number of stages and the characteristics of parallel machines at each stage. α field consists of four parameters as $\alpha_1, \alpha_2, \alpha_3,$ and α_4. α_1 demonstrates the general configuration of the shop, in this case a hybrid flowshop is denoted as HF. While α_2 indicates the number of stages in the shop, α_3 and α_4 represent the properties of the machines at each stage. The $(\alpha_3\alpha_4)^k$ notation shows that there are α_4 parallel machines with type of α_3 at stage k. $\alpha_3 \in \{\varnothing, P, Q, R\}$ where P, Q, and R indicate identical, uniform, and unrelated parallel machines, respectively. In case of $\alpha_3 = \varnothing$ there is a single machine in the given stage [56]. These machine environments have been briefly explained as follows [4].

- Identical parallel machines (P_m): All parallel machines have the same processing speeds, and therefore it is required the same processing times in these machines for each job.
- Uniform parallel machines (Q_m): Parallel machines have different production speeds, and processing times of jobs differ according to inversely proportional to the speed of the machine in these machines. This machine environment describes a special production system and less handled in research.
- Unrelated parallel machines (R_m): Parallel machines differ in terms of their speeds, and they have no relation with each other. The

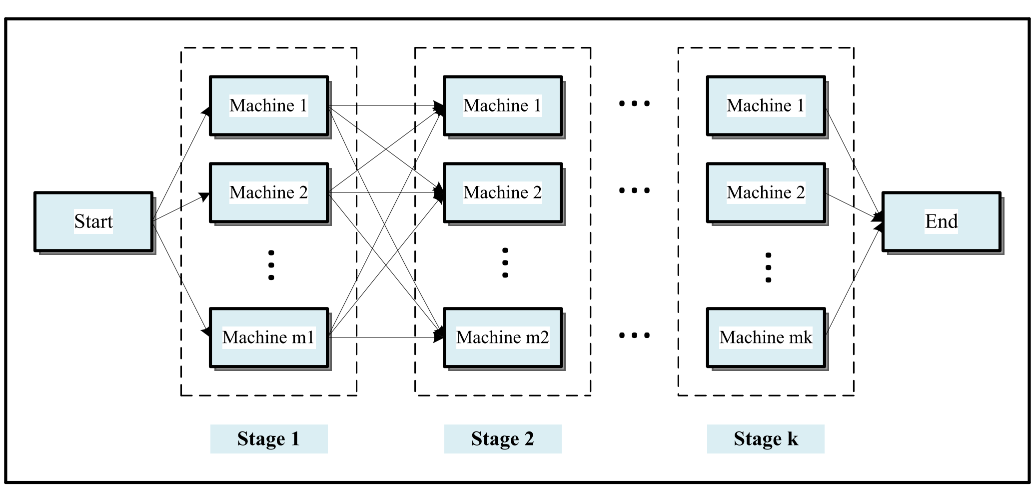

Fig. 1. The flowchart related to hybrid flowshop scheduling environment.

processing times of each job differ on different machines depending on the job-based processing speed.

Furthermore, the β field includes constraints and processing characteristics with respect to HFSPs. The most considered constraints in the HFSPs have been briefly explained in the following.

- Setup times: There can be two types of setup times as sequence-dependent and sequence-independent in the β field. In sequence-dependent setup times, the setup time is dependent on both of the successive jobs as a practical constraint of real manufacturing environments. Besides, in sequence-independent setup times, the setup times depend only on the processed job and are included in processing times [1].
- Stage skipping: This feature indicates the probability that job(s) may not undergo operations at some of the processing stages [58].
- Distributed scheduling: It is considered different factories in which there is an HFSP and as well as machine allocation and sequencing, it is required to select a factory for each job in distributed scheduling [4].
- Machine eligibility: This constraint states that the processing of a job is restricted to a set of predetermined machines at a stage due to technical or physical conditions [56].
- Lot streaming: This approach assists to split a given lot into smaller sublots, which can be processed and transported separately for simultaneous processing of successive operations in a multi-stage manufacturing system [59].
- Release dates: This constraint can be valid for both jobs and machines. For jobs, it indicates the earliest time that a job can be processed in a machine or stage, and in addition, it defines the time that a machine can be started to utilize due to technical requirements for machines [1].
- Blocking: It implies that the jobs must remain in the previous stage since there is zero or limited buffer between adjacent stages, and the machine is blocked until sufficient space is released [56].
- TOU electricity prices: It indicates that electricity prices may differ from hour to hour according to the time of day. It can be possible to provide cost savings by changing job processing times from on-peak periods (hours of high prices) to off-peak periods (hours of low prices) through the TOU electricity prices approach [60].
- Preventive maintenance: Machines generally undergo breakdown due to unexpected failures in real-life, and as an effective way, preventive maintenance contributes to prevent these failures and keeps machines in a good condition [61].
- Limited waiting times: This constraint indicates that the waiting time between two adjacent stages cannot be longer than a predetermined upper bound for all jobs [1].
- Multiprocessor task scheduling: It indicates the number of identical parallel processors required to process a job at a stage, and it is described with $size_{ij}$ [62].

On the other hand, various constraints such as transportation times, reentrant, variable speed levels, turn on/off strategy, learning/forgetting effect, new job arrival, machine breakdown, limited buffer, and time lag are also considered in the HFSPs.

The last parameter γ indicates the completion time-based, due date-based, environment-related, or cost-based criteria handled to be optimized in the HFSPs. The possible objective functions located in this field can be categorized as single-objective, bi-objective, or multi-objective (more than two objectives). Most real-life optimization problems include multiple objectives, and these are commonly conflicting and make the problems challenging to solve. There is no single optimal solution for the problems involving more than one conflicting objective [63].

Bi-objective and multi-objective problems can be converted to a single-objective problem with a priori approach using normal or weighted sum of two or more different objectives to solve more easily. Besides, with the posteriori approach, more than one objective can be optimized simultaneously by obtaining a set of non-dominated (Pareto optimal) solutions in these problems. The significant concepts utilized in the objective functions of HFSPs are given as follows. Where r_j and d_j demonstrate the release time and due date values for job j, respectively. The most utilized objectives for HFSPs have been presented in Table 1.

C_j: Completion time of job j in the last stage	T_j: Tardiness $T_j = \max(C_j - d_j, 0)$
F_j: Flow time $F_j = C_j - r_j$	E_j: Earliness $E_j = \max(d_j - C_j, 0)$
L_j: Lateness $L_j = C_j - d_j$	U_j: if job j is tardy 1, otherwise 0

3. Review methodology

In this study, the PRISMA methodology proposed by [64,65] has been utilized to realize a systematic review with respect to meta-heuristic algorithms applied for solving HFSPs. PRISMA statement includes four steps as identification, screening, eligibility, and included, and two main parts as systematic reviews and meta-analyses. Systematic reviews aim to provide a full overview related to research performed in a specific field for a determined time interval, and meta-analyses provide to present mathematical results obtained using statistical approaches for the reviewed articles. On the other hand, the main purpose of this methodology is to help researchers and practitioners to realize a detailed and focused literature review [66]. The flowchart related to our review process, consisting of the four steps of the PRISMA methodology, has been presented in Fig. 2.

In the identification phase, various keywords such as hybrid flow shop scheduling (HFSS), hybrid flowshop scheduling (HFS), flexible flow shop scheduling (FFSS), flexible flowshop scheduling (FFS), multiprocessor flow shop scheduling (MPFSS), and multiprocessor flowshop scheduling (MPFS) have been utilized to realize an extensive search in different academic databases with comprehensive searching areas such as Scopus (article title, abstract, keywords), Science Direct (find articles with these terms), Web of Science (all fields), Taylor & Francis Online (anywhere), and Wiley Online Library (anywhere). Thus, it has been aimed to make a detailed search in various academic databases using different versions of keywords. 3786 records have been identified as a result of database searching, and the search results based

Table 1
The most utilized objective functions for HFSPs [1].

Description	Explanation	Description	Explanation
$\max C_j$ ($C_{\max}$)	Maximum completion time	$\max E_j$ ($E_{\max}$)	Maximum earliness
$\sum C_j$	Total completion time	$\sum E_j$	Total earliness
$\sum C_j/n$	Mean completion time	$\sum E_j/n$	Mean earliness
$\sum w_j C_j$	Total weighted completion time	$\sum w_j E_j$	Total weighted earliness
$\max F_j$ ($F_{\max}$)	Maximum flow time	$\sum U_j$	Number of tardy jobs
$\sum F_j$	Total flow time	$\sum W_j$	Total waiting time
$\sum F_j/n$	Mean flow time	$\sum W_j/n$	Mean waiting time
$\sum w_j F_j$	Total weighted flow time	*TMIT*	Total machine idle time
$\max L_j$ ($L_{\max}$)	Maximum lateness	*AST*	Average sojourn time
$\sum L_j$	Total lateness	*TEC*	Total energy (electricity) consumption
$\sum L_j/n$	Mean lateness	*TECC*	Total energy (electricity) consumption cost
$\sum w_j L_j$	Total weighted lateness	*SC*	Setup cost
$\max T_j$ ($T_{\max}$)	Maximum tardiness	*PC*	Production cost
$\sum T_j$	Total tardiness	*WC*	Worker cost
$\sum T_j/n$	Mean tardiness	*IHC*	Inventory holding cost
$\sum w_j T_j$	Total weighted tardiness	*Othr*	Other specific objectives

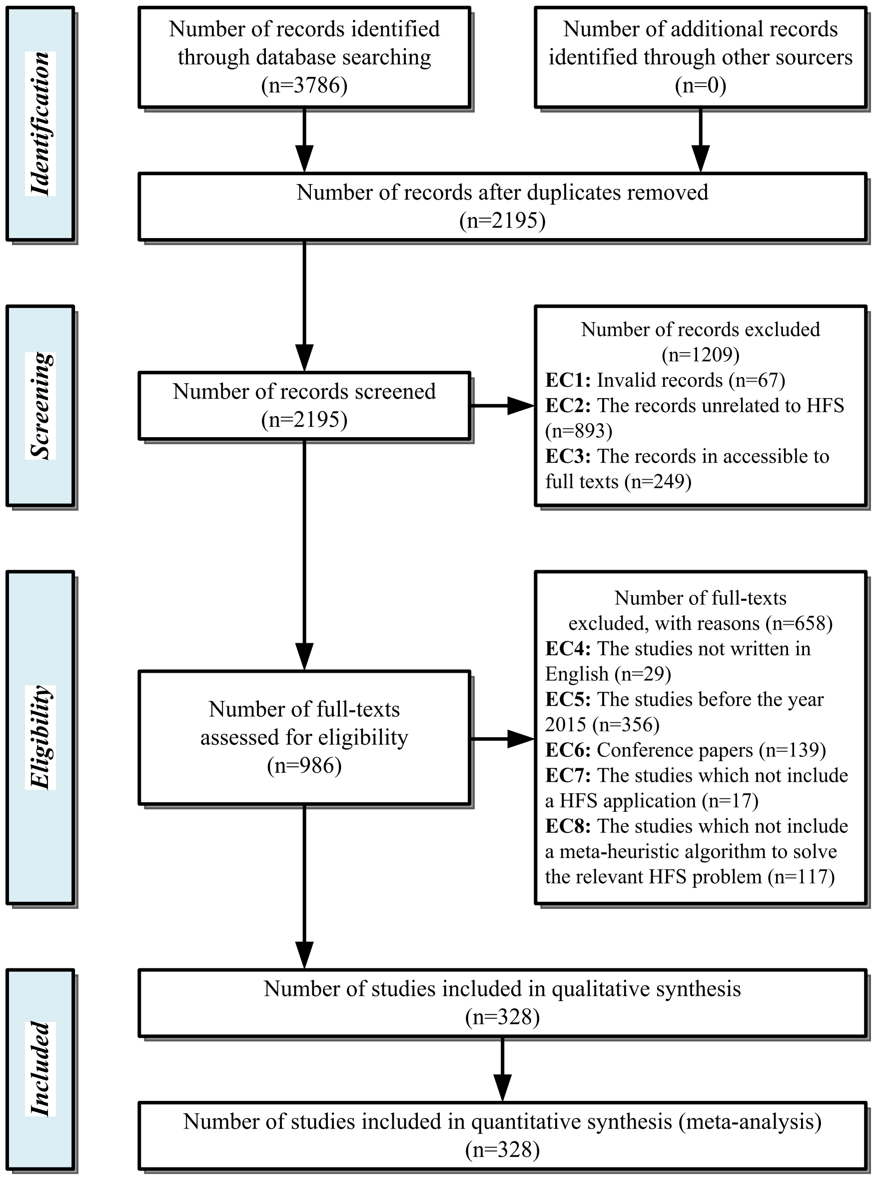

Fig. 2. The steps of review methodology.

on different keywords and academic databases have been presented in Table 2.

In the screening phase, in order to obtain more reliable analysis results, duplicated papers that came from different databases using keywords have been removed. Afterwards, some records have been eliminated from 2195 records through three exclusion criteria (EC1-EC3) as seen in Fig. 2. In the eligibility phase, the remaining 986 full-text papers have been assessed in terms of eligibility. Five exclusion criteria (EC4-EC8) with reasons as seen in Fig. 2 have been utilized to eliminate some of these papers. As a result, 328 articles have been determined for qualitative and quantitative analyses. In the last phase, 328 articles have been statistically and mathematically analyzed according to various features such as year, country, journal, publisher, objective functions, meta-heuristic algorithms, performance metrics, test instances, and parameter optimization methods. A summary classification related to the included articles has been presented in Table 3.

Table 2
The database searching results according to different keywords.

		Academic Databases					
		Scopus	Science Direct	Web of Science	Taylor & Francis Online	Wiley Online Library	Total
Results According to Keywords	**HFSS**	803	652	439	171	68	2133
	HFSS	240	215	184	59	19	717
	FFSS	214	247	151	75	28	715
	FFSS	40	67	33	15	7	162
	MPFSS	14	17	9	2	2	44
	MPFS	3	8	2	1	1	15
	Total	1314	1206	818	323	125	3786

A comprehensive summary of the included articles in which meta-heuristic algorithms are applied to solve HFSPs is presented in Table 3. The table aims to classify these articles according to several features, such as publication year, objective function, utilized meta-heuristic algorithm, performance metrics, test instances, and parameter calibration methods. In addition to providing a systematic overview of the current literature on HFSPs, it is possible to make some crucial and pragmatic inferences concerning research trends and gaps by means of the information given in this table.

Initially, a clear evolution is seen regarding the type of objective functions in the reviewed articles. The majority of earlier studies focus on single-objective formulations and the most widely utilized one is the minimization of makespan as a significant indicator of efficient system utilization. However, it is observed that there has been an obvious transition from single-objective problems through multi-objective optimization models to handle more realistic and complicated requirements of modern production environments in recent years. In this context, makespan is commonly optimized with other performance criteria such as total tardiness, total energy consumption, and total carbon emission. On the other hand, the increasing utilization of sustainability-related objectives demonstrates the growing effort to extend traditional efficiency-oriented scheduling models toward more comprehensive performance assessment approaches.

Secondly, analyzing the applied meta-heuristics shows that classical algorithms like GA, SA, and PSO are most commonly used to solve HFSPs due to their easy adaptability to complex optimization problems and well-established solution mechanisms. Recently, however, new-generation and hybrid meta-heuristic algorithms have gained significant attention in recent years. Hybrid approaches, in particular, are increasingly preferred because of their ability to balance exploration and exploitation, leading to better convergence. Furthermore, population-based algorithms dominate the literature over single-solution based meta-heuristics since they explore the search space more effectively and avoid premature convergence.

Thirdly, various performance metrics are effectively utilized in both single-objective and multi-objective HFSPs to evaluate the solution quality obtained from the meta-heuristic algorithms and to compare with the other algorithms. For single-objective problems, relative percentage deviation, objective value, and average relative percentage deviation are the three most prevalent performance measures. Similarly, inverted generational distance, set coverage, and hypervolume constitute the primary metrics utilized for performance comparison of multi-objective algorithms. In the context of utilized performance metrics, it is possible to say that the lack of standardized metrics makes it challenging to directly compare the efficiency and applicability of the proposed meta-heuristic algorithms.

As observed in Table 3, the test instances utilized in the included articles are classified into three main categories: randomly generated test problems (RGTPs), benchmark problems (BPs), and real case applications (RCAs). Randomly generated instances are typically employed when existing benchmark problems are insufficient due to the novelty of the problem specifically regarding machine environments, constraints, processing characteristics, and objectives. Since these test instances facilitate performance evaluation of algorithms under different scenarios, parameter analyses, and computational experiments on large-sized problems, they are extensively utilized to analyze and compare the proposed meta-heuristics in studies addressing the HFSP.

Finally, Table 3 demonstrates that various parameter tuning methods are utilized to enhance the performance of the meta-heuristic algorithms by contributing to determine the most appropriate parameter levels. Thus, these techniques support to avoid early convergence, to maintain diversity in the search space, and to intensify the search around promising regions. At this point, Taguchi is the most applied parameter calibration technique as a systematic approach since it enables researchers to determine the most suitable parameter levels with fewer experiments and thus to reduce computational cost. Preliminary tests are also commonly utilized rather than systematic approaches such as Taguchi method and full factorial design of experiment. Therefore, it is possible to say that parameter tuning will remain as a crucial indicator influencing the performance of meta-heuristic algorithms and will continue as an evolving aspect of algorithm design.

4. Descriptive statistical analysis of review results

In this section, we have performed descriptive statistical analyses related to the included articles examined in the scope of this review. These articles have been statistically and mathematically analyzed according to many features such as year, country, journal, publisher, objective functions, meta-heuristic algorithms, performance metrics, test instances, and parameter optimization methods. The analysis results have been presented via pie and bar charts for visual demonstration. Thus, it has been aimed to respond to predetermined research questions and provide a beneficial road map for researchers studying in this field. The defined research questions are given in the following.

RQ1: How the number of included articles is distributed according to years?

RQ2: In which countries are the researchers who study in the included articles addressed?

RQ3: In which journals are the included articles published?

RQ4: How the journals in which the included articles are published distributed according to publishers?

RQ5: How the included articles are distributed according to the type of objectives?

RQ6: Which objective functions are aimed to be optimized in the included articles?

RQ7: How is the trend for the number of bi-objective and multi-objective problems according to the years?

RQ8: Which are the most utilized meta-heuristic algorithms for solving HFSPs?

RQ9: How the meta-heuristic algorithms applied in the included articles are distributed according to the inspiration source and the number of solutions?

RQ10: Which performance metrics are utilized to evaluate solution quality in single-objective and multi-objective problems?

RQ11: Which types of test instances are utilized for the performance evaluation of meta-heuristics?

RQ12: Which methods are utilized for parameter optimization of meta-heuristic algorithms?

The yearly distribution of articles that include meta-heuristics for solving HFSPs has been presented in Fig. 3. As seen in this figure, the number of publications increases over the years with a positive trend in the (2015–2024) year interval, and a trendline with the coefficient of determination (R^2) = 0.84 has been obtained for the number of articles according to years. This R^2 value is highly upward, and it can be inferred that the utilization of meta-heuristic algorithms for solving HFSPs will grow rapidly. While the number of papers has reached to peak in 2024 with 55 publications, a new peak may be occurred in the next years according to this trendline. Since the HFSP has an NP-hard structure and many different application areas as a promising study field, it can be shown as a possible reason for the increasing trend in the number of publications in which meta-heuristics are applied to solve this type of scheduling problem.

A country-based analysis has been carried out to show the countries in which researchers applied meta-heuristic algorithms for solving HFSPs. In the scope of this analysis, the countries of each author have been considered as a separate contribution to the score of their countries when an article has more than one author from different countries. The top 10 countries whose authors mostly contribute to this research field have been presented in Fig. 4. As seen in this figure, the top 10 countries where the authors make the most publications in which meta-heuristics are utilized to solve HFSPs are China, Iran, USA, Taiwan, Turkey, United Kingdom, Canada, India, France, and Germany in descending order.

Table 3
A summary classification related to the included articles.

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[67]	2015	✓			$w_1 C_{max} + w_2 \sum C_j/n$	CS + Smallest position value rule	ARPD		✓	✓	
[68]	2015	✓			C_{max}	SA + Multiple search paths	Objective value; Computational time	✓			Preliminary tests
[69]	2015			✓	$\sum w_j T_j$; Total route selection cost; Total purchasing cost	NSGA-II; MOPSO	NPS; SM; QM	✓			
[70]	2015	✓			$w_1 \sum E_j + w_2 \sum T_j$	ACO + Flexible update	Effectiveness improvement; Robustness improvement	✓			Preliminary tests
[71]	2015	✓			$w_1 \sum E_j + w_2 \sum T_j$	Subgroup PSO	Effectiveness improvement; Robustness improvement	✓			Preliminary tests
[72]	2015	✓			$w_1 \sum W_j + w_2 \sum (E_j + T_j) + w_3$Adjusting cost	DE + VNDS + IBLS	RPD	✓			Taguchi
[73]	2015	✓			$\sum T_j$	GA + NEH + NS	RDI	✓			Preliminary tests
[74]	2015	✓			C_{max}	Discrete ABC; GA	RPD; Computational time	✓			Full factorial DOE
[75]	2015	✓			C_{max}	GWO + Lower bound heuristic	RPD	✓			Preliminary tests
[76]	2015	✓			C_{max}; $\sum w_j T_j$	GA + Heuristic rules	Computational time	✓			Full factorial DOE
[77]	2015	✓			C_{max}	ABC + TS	RPD	✓			Taguchi
[78]	2015	✓			$\sum F_j/n$; F_{max}	GA + OCBA	Objective value			✓	Preliminary tests
[79]	2015	✓			C_{max}	GA + Non-delay heuristic	Deviation	✓			Literature
[80]	2015	✓			C_{max}	SA + ICA	RPD	✓			Taguchi
[81]	2015	✓			C_{max}	GA + Relax-Blocking algorithm; PSO + Relax-Blocking algorithm	RPD	✓			Preliminary tests
[82]	2015	✓			Cycle time	GA + Heuristic; SA + Heuristic	RPD	✓			Full factorial DOE
[83]	2015	✓			$\lambda\ C_{max} + (1-\lambda)$dev of all the C_{max} values	Order-based EDA + OCBA	RPD; Standard deviation		✓		Taguchi
[84]	2015	✓			$\sum C_j$	GA + VNS; DE + VNS; EDA + VNS	RPD	✓			Taguchi
[85]	2015	✓			C_{max}	Discrete PSO + Mutation-based LS + Makespan heuristic	RPD		✓		Literature
[86]	2016	✓			$\sum T_j$	SA + Insertion algorithm	RPD	✓			Preliminary tests
[87]	2016	✓			$\alpha \sum w_j C_j + \beta \sum w_j T_j$	GA + GA; SA; TS	Deviation	✓			Full factorial DOE
[88]	2016	✓			C_{max}	SA + H_j algorithm	Computational time	✓			
[89]	2016	✓			$\sum w_j T_j$	GRASP + Bottleneck heuristic	RDI		✓		Full factorial DOE
[90]	2016	✓			C_{max}	Advanced compact GA + NEMAS	RPD	✓			Taguchi

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[91]	2016	✓			C_{max}	Cluster PSO	Effectiveness improvement Robustness improvement	✓			Literature Preliminary tests
[92]	2016		✓		$C_{max}; \sum w_j T_j$	ICA + VNS	Convergence metric; Δ; RDI	✓			Taguchi
[93]	2016	✓			C_{max}	AIS + ACO + LS	RPD	✓			
[94]	2016	✓			$w_1(AST) + w_2(\sum E_j) + w_3(\sum T_j) + w_4(\text{Skipping rate penalty})$	Discrete ABC + Enhanced LS	RPD	✓			Taguchi
[95]	2016	✓			$\sum w_j C_j$	GA; SA	Objective value; Computational time	✓			Preliminary tests
[96]	2016	✓			$w_1 C_{max} + w_2 \sum W_j$	CCABC	RPD	✓		✓	Full factorial DOE
[97]	2016	✓			$\sum T_j / n$	BBO	RPD	✓			Response surface methodology
[98]	2016	✓			$\sum w_j T_j$	VNS	RPD			✓	Taguchi
[99]	2016	✓			$\sum T_j / n$	GA; SA	RPD	✓			Experience
[100]	2016		✓		C_{max}; System unavailability	NSGA-II; NRGA; MOICA	QM; NPS; MID; RAS; SM	✓			Artificial neural networks
[101]	2016		✓		$C_{max}; \sum T_j$	TLBO + Insertion based LS + Equivalent due date-based permutation schedule strategy	Convergence metric; Δ; Ω		✓		Taguchi
[102]	2016		✓		C_{max}; TEC	Novel inertial weight PSO	ARPD; Computational time		✓		
[103]	2016	✓			$\alpha C_{max} + (1 - \alpha)TEC$	GA	Objective value	✓			
[104]	2016	✓			C_{max}	GA; ACO + Double pheremone	Deviation	✓			
[105]	2017	✓			$w_1 \sum E_j + w_2 \sum T_j + w_3$Missed orders + w_4Incomplete orders	Cloudy-based SA; AIS	ARPD	✓			Taguchi
[106]	2017	✓			C_{max}	GA + ACO	Heuristic performance	✓		✓	Fuzzy logic control
[107]	2017		✓		Maximization of throughput; Sum of delayed customer demand	NSGA-II + Customer first heuristic + System first heuristic	Convergence metric; Δ; Ω	✓			Literature
[108]	2017	✓			$C_{max}; \sum T_j; \sum U_j$	GRASP	Deviation		✓		
[109]	2017		✓		$C_{max}; \sum L_j / n$	Discrete MOIWO	DM; MID; RAS; QM	✓			Taguchi
[110]	2017	✓			C_{max}	GA + Four dispatching rules; SA	RPD; Computational time	✓			Preliminary tests
[111]	2017	✓			C_{max}	Improved FFO + SPT rule; Discrete ABC + Referenced LS; Improved MBO + Mixed neighborhood structure	RPD	✓			Full factorial DOE
[112]	2017	✓			PC + IHC + External acquisition cost	PSO + Heuristic methods	Objective value; Computational time	✓		✓	Taguchi
[113]	2017		✓		C_{max}; Unavailability of the system	NSGA-II; NSGA-II + 2-Opt LS	MID; SC; RAS; Computational time	✓			Preliminary tests
[114]	2017	✓			$\sum C_j$	MBO + Shortest waiting time rule + NS	RPD	✓			Taguchi

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[115]	2018	✓			The number of jobs that can be assigned to curing process 1	GA + A novel heuristic + A new crossover operator	Objective value; Computational time			✓	Preliminary tests
[116]	2018	✓			C_{max}	TLBO + JAYA	ARPD		✓		
[117]	2018		✓		C_{max}; $\sum w_j T_j$	MOVNS	HV; Epsilon metric; SM; Sphere counting		✓		
[118]	2018	✓			$\sum(\alpha_j E_j + \beta_j T_j)$	MA	Objective value		✓		Full factorial DOE
[119]	2018		✓		TEC; $\sum T_j$	TLBO	DI_R; Metric ρ	✓			Preliminary tests
[120]	2018	✓			C_{max}	Discrete ABC + Scout bee strategy	RPD	✓			Taguchi
[121]	2018		✓		C_{max}; TEC	Energy-aware multi-objective algorithm	Rnd metric; Average pareto distance; NNDS	✓	✓		Preliminary tests
[122]	2018		✓		C_{max}; TEC	NSGA-II		✓			Preliminary tests
[123]	2018	✓			$w_1 C_{max} + w_2 \sum W_j + w_3$Total processing time deviation	Improved GA	ARPD	✓			Taguchi
[124]	2018	✓			C_{max}; $w_j C_j$; $w_j T_j$	GA	Heuristic performance	✓			
[125]	2018		✓		C_{max}; $\sum T_j$	NSGA + Data envelopment analysis	NPS; QM; MID; SNS; Triangle method; Free disposal hull approach	✓			Taguchi
[126]	2018	✓			$w_1 AST + w_2 \sum E_j + w_3 \sum T_j$	ABC + VNS + Population initialization heuristic	RPD	✓			Taguchi
[127]	2018	✓			$w_1 AST + w_2 \sum E_j + w_3 \sum T_j + w_4$Cast break $+ w_5$Starting time difference $+ w_6$The number of operations	ABC + Population initialization heuristic	RPD	✓		✓	Taguchi
[128]	2018	✓			C_{max}	ACO	Objective value; Computational time	✓			Preliminary tests
[129]	2018	✓			$\sum w_j T_j$	VNS + Time window decomposition scheme	Improvement	✓			Full factorial DOE
[130]	2018		✓		C_{max}; Total carbon footprint	NSGA-II + Variable LS	Objective value; NPS			✓	
[131]	2018	✓			C_{max}	Self tuning IGA	ARPD	✓			Preliminary tests
[132]	2018	✓			$\sum T_j$	GA	RDI	✓			Full factorial DOE
[133]	2018			✓	C_{max}; TEC; Total material wastage	NSGA-II + TS + A job merging strategy	HV	✓			
[134]	2018	✓			$\sum T_j$	Discrete DE	ARPD	✓			Preliminary tests
[135]	2018	✓			$w_j C_j$	DE + EDA	RPD	✓			Preliminary tests
[61]	2019	✓			C_{max}	GA	RPD	✓			Taguchi
[136]	2019	✓			C_{max}	Diversified PSO	RPD	✓			Literature
[137]	2019	✓			C_{max}	PSO; SA + PSO	RPD; Deviation	✓			Full factorial DOE
[138]	2019	✓			$\sum(\alpha_j E_j + \beta_j T_j)$	Immunoglobulin-based AIS + Priority of Earliness and Tardiness rule	RDI	✓			Preliminary tests
[139]	2019		✓		Product assembly timeliness; On-time product delivery time	Mutant FA		✓			

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[140]	2019	✓			C_{max}	ICA + GA			✓		Full factorial DOE
[141]	2019			✓	C_{max}; T_{max}; Idle energy consumption	Improved MOMVO	SM; GD; IGD		✓		Taguchi
[142]	2019	✓			$\sum T_j$	PSO; PSO + SA	RPD	✓			Preliminary tests
[143]	2019	✓			$\alpha \sum C_j + (1-\alpha) L_{max}$	GA + LS + Clustering; PSO + LS + Clustering	RPD	✓			Taguchi
[144]	2019	✓			C_{max}; TMIT; Total plant *factor*; Total workpiece blockage time	SA + HNN algorithm + Local scheduling rules	Deviation	✓	✓	✓	
[145]	2019	✓			C_{max}; $\sum W_j$; Total machine setup *time*; Total job blocking time	WOA + SA + Levy flight + Opposition based learning strategy	Objective value	✓			
[146]	2019	✓			C_{max}; *TMIT*; $\sum W_j$; Total device *availability*; Total machine setup *time*; Total job blocking time	GA + Local dispatching rules	Objective value; Computational time		✓	✓	Taguchi
[147]	2019	✓			C_{max}	BSO + NEH + K-means clustering	RPD	✓			Taguchi
[148]	2019		✓		Total cost; The kilograms of CO_2	Pareto based hybrid GA	HV			✓	
[149]	2019	✓			$\sum w_j E_j + \sum w_j T_j$	SS + VNS; Opposition-based WOA; Discrete GWO	RPD	✓			Taguchi
[150]	2019	✓			C_{max}	ACO + Non-DaemonActions procedure	ARPD		✓		Literature Preliminary tests
[151]	2019			✓	$\sum T_j$; C_{max}; TEC	ICA	DI_R; SC	✓			Taguchi
[152]	2019	✓			C_{max}	EDA + DE	RPD	✓			Taguchi
[153]	2019			✓	C_{max}; *TEC*; Noise pollution	GWO + VNS + Cellular automata	Δ; GD; IGD	✓	✓		Preliminary tests
[154]	2019	✓			$\sum T_j$	Island GA	Objective value; Computational time	✓			Literature
[155]	2019	✓			$w_1 \sum T_j + C_{max}$	GA + A predictive reactive complete rescheduling strategy	Objective value; Computational time	✓			Full factorial DOE
[156]	2019	✓			TEC	Improved GA	RPD; ARPD	✓			Taguchi
[157]	2019	✓			$\sum C_j$	IGA + CH; VBIH	RPD; Computational time	✓	✓		Full factorial DOE
[158]	2019	✓			C_{max}	ACO + LS	Objective value			✓	Preliminary tests
[159]	2019	✓			C_{max}	GA + SA; PSO + SA	RPD	✓			Taguchi
[160]	2019	✓			$\sum C_j$	GA + Simulation; SA + Simulation; PSO + Simulation	ARPD	✓			Response surface methodology
[161]	2019			✓	C_{max}; *TECC*; Peak power	Multiphase ILS	NNDS; HV	✓			Full factorial DOE
[162]	2019		✓		$\sum T_j$; Machine idle rate	NSGA-II		✓			Preliminary tests
[163]	2019	✓			$\sum w_j C_j$	ABC + GA + VNS + Greedy heuristic	ARPD	✓			Taguchi

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[164]	2019		✓		C_{max}; TEC	ABC + VND + TOPSIS	SC; Δ; IGD; NNDS	✓			Taguchi
[165]	2019	✓			$\sum T_j$	DE + PSO + Kalman filter + Multi-stage learning strategy	Deviation	✓			Taguchi
[166]	2019		✓		C_{max}; TEC	ICA + Empire grouping	SC; Metric ρ	✓			Taguchi
[167]	2019	✓			IHC + SC	FFO + Dispatching rules	RPD	✓			Taguchi
[168]	2019	✓			IHC + SC	ILS + Approximate function	RPD	✓			Full factorial DOE
[62]	2020	✓			C_{max}	MA + LS + NEH	ARPD		✓		Full factorial DOE
[169]	2020	✓			C_{max}	Multi-agent IA	RPD	✓			
[170]	2020	✓			C_{max}	Improved GA + 2-opt LS	ARPD	✓			Preliminary tests
[171]	2020	✓			C_{max}	Dynamic SFLA + Global search + Multiple neighborhood search	RPD		✓		Literature
[172]	2020		✓		C_{max}; TECC	Tailored SPEA-II	Δ; IGD	✓		✓	
[173]	2020		✓		C_{max}; TEC	NSGA-II + MOEES	SC; SM; Maximum spread; Distance metrics; NNDS	✓			
[174]	2020		✓		C_{max}; TEC	PESA-II; SPEA-II; NSGA-II	NNDS; SC			✓	Full factorial DOE
[175]	2020	✓			C_{max}	TS + Backtracking search algorithm	ARPD	✓			Full factorial DOE
[176]	2020			✓	C_{max}; $\sum w_j T_j$; $\sum w_j E_j$	VNS + GRASP	HV; Epsilon metric; SM		✓		Preliminary tests
[177]	2020			✓	C_{max}; Total carbon *emission*; Total preventive maintenance cost	NSGA-II + MVO	SM; GD; IGD	✓			Taguchi
[178]	2020			✓	C_{max}; Total noise *pollution*; Total dust pollution	Discrete MOROA	SC; NNDS; Δ; MRDI	✓			
[179]	2020		✓		C_{max}; $\sum T_j$	MOEA + Bi-population strategy	SC; IGD; HV	✓			Orthogonal experiment
[180]	2020		✓		C_{max}; TEC	Improved MOALO	IGD; Ω; Δ		✓		
[181]	2020			✓	C_{max}; $\sum T_j$; Workload balance of workers	Improved MOMA	IGD; Ω; SM	✓			Taguchi
[182]	2020	✓			C_{max}	EHO	RPD	✓			Taguchi
[183]	2020			✓	C_{max}; Total *WC*; Green production indicator	EA + VNS	SC; IGD		✓		Taguchi
[184]	2020	✓			C_{max}	Improved MBO	RPD; ARPD	✓			Taguchi
[185]	2020		✓		TEC; Total PC	NSGA-II + Heuristic procedure for initial solution	ONVG; SM; DM; MID	✓			Taguchi
[186]	2020			✓	C_{max}; Machine *deviation*; Total transportation time	NSGA-III	MID; SNS; POD			✓	
[187]	2020	✓			$\alpha(C_{max}) + \beta(\text{TEC}) + \gamma(\text{Total PC})$	Improved GA	Quasi optimal solutions; Convergence time	✓			
[188]	2020	✓			C_{max}	IGA + Earliest completion time with transportation	RPD	✓			Full factorial DOE
[189]	2020		✓		C_{max}; $\sum U_j$	SFLA + Memeplex grouping	DI_R; SC	✓			Preliminary tests

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[190]	2020			✓	AST; TEC; $\sum E_j$; $\sum T_j$	MOEA/D + Problem specific heuristics	HV; IGD	✓	✓		Full factorial DOE
[191]	2020		✓		C_{max}; Total PC	Improved ABC	MID; SNS; POD			✓	Taguchi
[192]	2020	✓			C_{max}	ABC + SA + NS + Dispatching rules	RPD	✓			Taguchi
[193]	2020	✓			$w_1 C_{max} + w_2 \sum F_j/n$	HS + GA	RPD			✓	Preliminary tests
[194]	2020		✓		C_{max}; TECC	Bi-objective DE	IGD; SC; Maximum spread; NNDS	✓			Preliminary tests
[195]	2020	✓			$w(C_{max}) + 1 - w(TEC)$	EA	Objective value			✓	Experience
[196]	2020	✓			$w_1 C_{max} + w_2 \sum (C_j - r_j)$	PSO + VNS + NEH + SPT	ARPD	✓		✓	Full factorial DOE
[197]	2020	✓			C_{max}	EDA	Objective value			✓	
[198]	2020		✓		C_{max}; TEC	IGA + NEH; VBIH + NEH	Rnd metric; IGD; Distribution spacing	✓			Literature Preliminary tests
[199]	2020	✓			C_{max}	Improved FA	Objective value	✓			Literature
[200]	2020	✓			C_{max}	MBO	RPD			✓	Preliminary tests
[201]	2020	✓			C_{max}	IGA + Multi-neighborhood LS	ARPD	✓			Full factorial DOE
[202]	2020	✓			C_{max} + Delay cost	DE + LS	RPD; Standard deviation	✓			
[203]	2020	✓			C_{max}	Discrete ICA + SA	RPD	✓			Taguchi
[204]	2020			✓	C_{max}; Total agreement *index*; TEC	SFLA + Multiple search strategies	SC; Metric ρ	✓			Taguchi
[205]	2020	✓			C_{max}	Improved MBO + NS	RPD	✓			Taguchi
[206]	2020	✓			C_{max}	GA + Two-stage heuristic	RPD	✓			Preliminary tests
[207]	2020		✓		C_{max}; TEC	TS + CH; ACO + CH	NNDS; SM; DI_R	✓		✓	Chess rating system
[208]	2020		✓		C_{max}; TEC	TMOA/D	Δ; GD; IGD; NPS	✓			Preliminary tests
[209]	2020		✓		$\sum T_j$; Robustness	EDA + IG Search	ONVG; SC; SM	✓			Taguchi
[8]	2021		✓		C_{max}; $\sum C_j$	MOHS + Gaussian mutation + CH + Clustering	QM; MID; RAS; SC; DM	✓		✓	Response surface methodology
[11]	2021			✓	C_{max}; TECC; WC	Two-phase GA	Two-sample one-tailed t test		✓	✓	
[12]	2021			✓	C_{max}; TEC; Total handling distance	MOEA/D + LS	IGD; HV	✓			Literature Preliminary tests
[59]	2021	✓			C_{max}	Collaborative VND	RPD		✓		Taguchi
[60]	2021		✓		$\sum T_j$; TECC	PSO + TS + LS	Converging time; NNDS; SC; GD; SM	✓			Literature
[210]	2021	✓			C_{max}	PSO; SA + PSO	RPD; Computational time	✓			
[211]	2021	✓			$\sum E_j + \sum T_j$	WWOA + MBO	ARPD	✓			Preliminary tests
[212]	2021	✓			$\sum T_j$	SA + CH; TS + CH	Heuristic performance; Computational time	✓			Full factorial DOE

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[213]	2021			✓	C_{max}; *TEC*; Total aggrement index	Cooperated SFLA	SC; Metric ρ; IGD	✓			Taguchi
[214]	2021		✓		C_{max}; $\sum T_j$	SFLA + Memeplex quality	DI_R; SC	✓			Taguchi
[215]	2021	✓			C_{max}	Improved GS	Objective value; Computational time		✓	✓	Taguchi
[216]	2021	✓			Total tardiness cost + PC + Outsourcing cost	SA; GA; PSO; PSO + SA	RPD	✓			Taguchi
[217]	2021		✓		$\sum T_j$; Total quality cost	MOABC + Stochastic simulation approach	SC; IGD; HV	✓			Taguchi
[218]	2021	✓			C_{max}	Hybrid pointer-based DE	Objective value; Computational time	✓			
[219]	2021		✓		C_{max}; $\sum T_j$	MOEA + Heuristic decoding	IGD; NNDS; Rnd metric	✓		✓	
[220]	2021	✓			C_{max}	ACO	Objective value; Computational time	✓			Preliminary tests
[221]	2021		✓		C_{max}; TEC	Improved MOEA/D	SC; T-metric		✓		Taguchi
[222]	2021		✓		C_{max}; $\sum T_j$	NSGA-II + MBO	IGD; SM	✓			Full factorial DOE
[223]	2021	✓			C_{max}	BSO + NEH + LS + SA based acception criterion	RPD	✓			Taguchi
[224]	2021		✓		C_{max}; TEC	Discrete ABC	NNDS; IGD; SC	✓			
[225]	2021	✓			C_{max}	ABC + NEH + Average factory assignment	RPD	✓			Taguchi
[226]	2021		✓		$\sum (E_j + T_j$; $\sum W_j$	Modified GA	Performance improvement rate	✓			Full factorial DOE
[227]	2021			✓	C_{max}; Average energy *consumption*; Fluctuation of energy consumption and production	MOEA/D + VNS	GD; SM; IGD	✓			Taguchi
[228]	2021	✓			C_{max}	Chaos-enhanced SA	ARPD		✓		Taguchi
[229]	2021	✓			C_{max}	SA + Discrete-event simulation	Objective value			✓	Taguchi
[230]	2021			✓	C_{max}; $\sum (w_jE_j + w_jT_j)$; Total workload	MOEA + LS	HV; Unary epsilon metric	✓			Full factorial DOE
[231]	2021			✓	C_{max}; *TEC*; Total carbon emission	GA-based dynamic scheduling optimization	Objective value; Computational time	✓			Preliminary tests
[232]	2021		✓		C_{max}; TEC	Hybrid MOTLBO	IGD; Rnd metric	✓			Taguchi
[233]	2021	✓			C_{max}	Bi-population cooperative MA	RPD	✓			Taguchi
[234]	2021	✓			C_{max}	ABC + Adaptive NS	Objective value	✓			
[235]	2021		✓		C_{max}; TEC	Improved MOWOA	Δ; GD; IGD	✓		✓	Taguchi
[236]	2021	✓			C_{max}	Discrete WSA	Objective value			✓	Preliminary tests
[237]	2021	✓			$\lambda C_{max} + (1 - \lambda) \sum T_j$	GA + VNS + SA + NEH + CDS	ARPD	✓			Preliminary tests
[238]	2021			✓	C_{max}; $\sum T_j$; TEC	Multi-population ABC	DI_R; SC; NNDS		✓	✓	Taguchi
[7]	2022	✓			C_{max}	GA + VNS	Objective value			✓	Taguchi

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[13]	2022		✓		C_{max}; Comprehensive resource and environmental impact	Improved MFOA	Convergence index; SNS; POD			✓	
[239]	2022	✓			C_{max}	Parallel GA; Parallel PSO; Parallel ACO; Parallel PSO + GA	Deviation	✓			Taguchi
[240]	2022		✓		C_{max}; $\sum T_j$	Collaborative VNS	Metric ρ; SC; IGD	✓			Full factorial DOE
[241]	2022		✓		C_{max}; TECC	MOEA/D + Enhanced NEH	Deviation	✓		✓	Preliminary tests
[242]	2022		✓		C_{max}; TEC	NSGA-II + Enhanced NEH	Deviation	✓		✓	Preliminary tests
[243]	2022			✓	C_{max}; *TECC*; Total carbon emission	NSGA-III + SSA	SM; IGD; Ω	✓		✓	Taguchi
[244]	2022		✓		C_{max}; Total carbon emission	NSGA-II + MFOA	GD; IGD	✓		✓	Full factorial DOE
[245]	2022		✓		$\sum W_j$; $\sum C_j/n$	MOSA; MOEA/D	NPS; DM; MID; SNS; Computational time	✓			Taguchi
[246]	2022		✓		C_{max}; TECC	MOABC	IGD; SC	✓			Taguchi
[247]	2022	✓			C_{max}	GA-based approaches	RPD	✓			Preliminary tests
[248]	2022	✓			C_{max}	GA; SA; Enhanced PSO	Coefficient of variation; Objective value; Computational time	✓			Taguchi
[249]	2022		✓		C_{max}; Total PC	NSGA-II	ONVG; SM; MID; DM	✓			Taguchi
[250]	2022	✓			C_{max}	GA	Deviation; Computational time	✓			Preliminary tests
[251]	2022	✓			C_{max}	GA + ACO + SA	Objective value; Computational time	✓			Preliminary tests
[252]	2022		✓		C_{max}; TEC	KMOEA	HV; IGD	✓			Full factorial DOE
[253]	2022	✓			C_{max}	GA + TS	Objective value	✓			
[254]	2022			✓	C_{max}; TEC; Maximum excess of adjustment time	ASMOAP	IGD	✓			
[255]	2022		✓		C_{max}; TEC	MOHIG	GD; IGD; Δ	✓			Taguchi
[256]	2022	✓			TEC	Efficient adaptive GA	RPD	✓			
[257]	2022	✓			C_{max}	GA + GRASP	RPD	✓			Taguchi
[258]	2022	✓			$\sum \left(w_j E_j + w'_j T_j \right)$	Parameter-Less IGA	ARDI		✓		Full factorial DOE
[259]	2022	✓			C_{max}	GA	RPD	✓			Preliminary tests
[260]	2022	✓			C_{max}	IGA	RPD; Objective value; Computational time	✓			Taguchi
[261]	2022	✓			C_{max}	Collaborative IGA	RPD	✓			Full factorial DOE
[262]	2022	✓			TEC	IGA	RPD	✓			Preliminary tests
[263]	2022		✓		C_{max}; TEC	TTA	Wilcoxon signed-rank test		✓	✓	Literature
[264]	2022		✓		$\sum w_j T_j$; TEC	MOMA + Weighted NEH	HV; Unary epsilon metric; SC	✓			Full factorial DOE

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[265]	2022			✓	$\sum T_j$; Total *PC*; Total carbon emission	Network MA	HV; Unary epsilon metric; IGD	✓			Full factorial DOE
[266]	2022		✓		C_{max}; TEC	ACO behavior-based MOEA/D	HV; Unary Epsilon metric; IGD; SC	✓			Full factorial DOE
[267]	2022	✓			Productivity maximization	Adaptive RKGA	Objective value; Computational time	✓			
[268]	2022	✓			C_{max}	Self-adaptive ABC	RPD	✓			Taguchi
[269]	2022	✓			TEC	AO + TS	Objective value; Computational time			✓	Full factorial DOE
[270]	2022	✓			TEC	AOA + NS	Objective value	✓			Full factorial DOE
[271]	2022		✓		C_{max}; TEC	Cooperative MA	ONVG; SC; HV; DI_R		✓		Taguchi
[272]	2022		✓		C_{max}; TEC	ACO + GA	SC; HV	✓			Taguchi
[273]	2022		✓		C_{max}; TEC	Improved MOEA/D	HV; GD; SM	✓			Taguchi
[274]	2022		✓		C_{max}; TEC	Improved MOEA/IOD	HV; GD; IGD	✓			Preliminary tests
[275]	2022		✓		The difference between the actual output and the target output; $\sum W_j$	Improved MOEA/D	HV; GD; IGD	✓			Taguchi
[276]	2022		✓		C_{max}; Total number of sublots	MOEA + Automatic algorithm design	SC; IGD; NNDS	✓			Automated algorithm design
[277]	2022	✓			$\sum C_j$	MBO + VND	RPD	✓			Taguchi
[3]	2023		✓		C_{max}; $\sum U_j$	Dual population GA + Q-learning	Metric ρ; SC; IGD	✓			Taguchi
[5]	2023		✓		*TECC*; $\sum C_j$	Tailored SPEA-II	Δ; IGD			✓	
[6]	2023		✓		$\sum w_j T_j$; TEC	Pareto SMO	GD; IGD; SM	✓		✓	Preliminary tests
[9]	2023	✓			C_{max}	Multi-population MA + Q-learning	RPD	✓		✓	Taguchi
[278]	2023	✓			TECC + Total tardiness cost	Multi-layer encoding GA	Objective value			✓	
[279]	2023	✓			$\sum w_j T_j$ for scheduled orders; The total number of unscheduled orders; Total PC	Random multi-start algorithm + CH; Biased RKGA + CH; VNS + CH	ARPD	✓			Irace (Iterated racing for automatic algorithm configuration) package
[280]	2023	✓			C_{max}	SFLA + Q-learning	RPD	✓		✓	Taguchi
[281]	2023	✓			C_{max}	Improved multi-population GA	RPD; ARPD	✓		✓	Taguchi
[282]	2023		✓		C_{max}; $\sum T_j$	SMO + GA	IGD; Rnd metric	✓			Taguchi
[283]	2023	✓			C_{max}	Hybrid EA + TS	RPD	✓			Taguchi
[284]	2023		✓		C_{max}; Number of handling events	NSGA-II + VNS	ARPD; Standard deviation	✓			Full factorial DOE
[285]	2023		✓		C_{max}; TEC	Improved HPAEA	HV; IGD	✓			Literature
[286]	2023		✓		C_{max}; TECC	Improved NSGA-II	HV; IGD	✓			Taguchi

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[287]	2023	✓			C_{max}	Multi-crossover-operator GA	Objective value; Computational time	✓			
[288]	2023	✓			C_{max}	TS + Neighborhood structure	RPD	✓			Preliminary tests
[289]	2023		✓		C_{max}; Total Cost	Pointer-based discrete DE	Objective value; Computational time		✓		Preliminary tests
[290]	2023	✓			C_{max}	EMA	Objective value; Computational time	✓			
[291]	2023	✓			C_{max}	Cooperative SFLA	RPD	✓			Taguchi
[292]	2023		✓		C_{max}; T_{max}	Multi-class TLBO	DI_R; SC	✓			Preliminary tests
[293]	2023	✓			TEC	CCEA + VND	RPD	✓			Taguchi
[294]	2023	✓			w_1C_{max} + w_2Transport time + w_3(Imbalance degree of team workload) + w_4(Imbalance degree of cycle time)	GA + SA + Improved NEH	Wilcoxon signed-rank test	✓			Taguchi
[295]	2023			✓	$\sum T_j$; TECC; Carbon trading cost	NSGA-II + VNS + Q-learning	SC; NPS; SM	✓			Taguchi
[296]	2023		✓		$\sum w_jT_j$; TEC	Double deep Q-Learning based co-evolution	HV; GD; Δ	✓			Taguchi
[297]	2023		✓		C_{max}; TEC	CBMA	HV; IGD	✓			Taguchi
[298]	2023	✓			C_{max}	Improved CS	RPD	✓			Taguchi
[299]	2023			✓	Workload balance of assembly processes; Workload balance of assembly lines; Reconfiguration and assembly costs; Storage costs of raw materials; Warehousing costs of end-products	MOHHO	MID; Maximum spread; SM	✓			Preliminary tests
[300]	2023	✓			C_{max}	EDA + Multiple intensification strategies	ARPD	✓			
[301]	2023	✓			C_{max}	GA + Reinforcement learning	Objective value	✓			Preliminary tests
[302]	2023	✓			C_{max}	Heuristic-based adaptive IGA	RPD		✓	✓	Taguchi
[303]	2023		✓		C_{max}; TEC	Improved MOEA/D	Rnd metric; IGD	✓			Taguchi
[304]	2023		✓		C_{max}; (TECC + WC)	Adjusted MOGA	SM; DM; QM; IGD; MID	✓			Taguchi
[305]	2023		✓		C_{max}; $\sum T_j$	MOGA	NPS		✓		Taguchi
[306]	2023		✓		C_{max}; TEC	NSGA-III	Pareto percentage; Error ratio; GD; IGD; SM; Maximum spread; Normalized HV		✓	✓	Preliminary tests
[307]	2023	✓			TEC	Improved IGA	RPD	✓			Preliminary tests
[308]	2023	✓			C_{max}	Improved MA	RPD	✓			
[309]	2023	✓			C_{max}	ILS + NEH + LS	ARPD	✓			Full factorial DOE
[310]	2023	✓			C_{max}	GA + IGA + Eight new heuristics + VND-based LS	ARPD	✓			Full factorial DOE
[311]	2023	✓			α_1C_{max} + α_2TEC	Dual-population GA	Deviation	✓			Taguchi
[312]	2023		✓		C_{max}; TEC	MOABC/D	GD; IGD; SC; NNDS	✓			Taguchi

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[313]	2023		✓		C_{max}; TEC	Adaptive MOHHO	IGD; Δ; GD	✓		✓	Taguchi
[314]	2023	✓			C_{max}	Variant IGA	ARPD	✓			Taguchi
[315]	2023	✓			C_{max}	Advanced IGA	RPD; ARPD	✓			Taguchi
[316]	2023		✓		C_{max}; TEC	Fuzzy correlation entropy based NSGA-II	IGD	✓			Taguchi
[317]	2023		✓		C_{max}; TEC	Extended NSGA-II	IGD	✓			Taguchi
[318]	2023		✓		$\sum\left(w_j^E E_j + w_j^T T_j\right)$; Lost order quantity	Improved NSGA-II	IGD; HV; SC	✓			Full factorial DOE
[319]	2023			✓	C_{max}; *TEC*; Total starting time deviation	MOFA + VNS	GD; IGD; Δ	✓			Literature
[320]	2023		✓		C_{max}; TEC	Improved MA	IGD; SC	✓			Taguchi
[321]	2023		✓		C_{max}; Transferring cost	MOEA/D + LS	HV; IGD; GD; SC	✓			Taguchi
[322]	2023	✓			$w_1 C_{max} + w_2$(Number of fixtures)	ACO	Objective value			✓	Taguchi
[323]	2023	✓			C_{max}	ABC + VNS + Problem-specific heuristic	RPD	✓			Preliminary tests
[324]	2023	✓			C_{max}	PSO based on ATCM	Computational time	✓			Literature
[325]	2023			✓	$\sum C_j$; Total starting time *deviation*; Average adjustment of sublot sizes	MMBO/D	Δ; GD; IGD	✓			Taguchi
[326]	2023		✓		C_{max}; TEC	Population diversity-based ABC	IGD; SC	✓		✓	Taguchi
[2]	2024	✓			C_{max}	MRLM	RPD	✓	✓		Full factorial DOE
[28]	2024	✓			C_{max}	Discrete ABC	Objective value		✓	✓	Taguchi
[55]	2024		✓		C_{max}; Due time deviation	Knowledge-based MA	GD; IGD; HV	✓		✓	Taguchi
[327]	2024		✓		C_{max}; TEC	SFLA + Q-learning	GD; SM; Δ		✓✓		Taguchi
[328]	2024		✓		C_{max}; Evaluation index	NSGA-II	Objective value; Computational time			✓	Preliminary tests
[329]	2024	✓			$w_1 C_{max} + w_2$(Equipment utilization)	Improved PSO	Objective value; Computational time; Equipment utilization rate	✓		✓	Preliminary tests
[330]	2024		✓		C_{max}; TEC	Two-stage adaptive MA	HV; GD; Δ	✓			Taguchi
[331]	2024			✓	C_{max}; *TEC*; $\sum T_j$	Cooperative GWO	IGD; ONVG	✓			Taguchi
[332]	2024		✓		C_{max}; TEC	MOEA/D	Objective value	✓			Preliminary tests
[333]	2024		✓		C_{max}; $\sum T_j$	Multi-population GA	Δ; GD; IGD	✓		✓	Taguchi
[334]	2024	✓			ρ_1(Tardiness cost) + ρ_2(TEC)	GA + Reinforcement learning	RPD; Coefficient of variance	✓			
[335]	2024			✓	C_{max}; TEC; Delivery accuracy	EDA + Reinforcement learning	HV; SC; GD	✓			Taguchi
[336]	2024			✓	T_{max}; Idle energy *consumption*; C_{max}	GP + Hyper heuristic	ARPD	✓			Preliminary tests

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[337]	2024		✓		C_{max}; Time deviation before and after rescheduling	Improved MOEA	IGD; HV	✓			Preliminary tests
[338]	2024	✓			Carbon footprint	PIOA + FA	ARPD	✓		✓	Literature
[339]	2024			✓	C_{max}; $\sum C_j/n$; Total workload imbalance	NSGA-II	DI_R; SC; Overall pareto spread; NNDS	✓			Preliminary tests
[340]	2024	✓			C_{max}	SA	RPD	✓			Preliminary tests
[341]	2024	✓			C_{max}	Improved GA	ARPD; Computational time	✓			Taguchi
[342]	2024	✓			C_{max}	Q-learning hyper-heuristic EA + Reinforcement learning	RPD	✓			Taguchi
[343]	2024	✓			C_{max}	Improved GA	Objective value; Computational time	✓			Preliminary tests
[344]	2024	✓			C_{max}	TSCNSA	RDI; RPD		✓		Full factorial DOE
[345]	2024	✓			C_{max}	Elite-class TLBO	RPD	✓			Taguchi
[346]	2024		✓		C_{max}; TEC	Adaptive two-class TLBO	SC; Metric ρ; DI_R		✓✓		Taguchi
[347]	2024	✓			Total penalty	Collaborative IGA	RPD	✓			Preliminary tests
[348]	2024	✓			C_{max}	DGSK	RPD	✓			Taguchi
[349]	2024			✓	C_{max}; *TEC*; Total machine workload	Improved MOMBO	IGD; MID; RAS	✓		✓	Taguchi
[350]	2024			✓	Average processing time; Matching degree; Oxygen consumption fluctuation	NSGA-II + VNS + TOPSIS	IGD	✓			Taguchi
[351]	2024	✓			C_{max}	Tri-individual IGA	RPD; ARPD	✓			Full factorial DOE
[352]	2024	✓			C_{max}	Multitasking MA	ARPD	✓			Taguchi
[353]	2024	✓			C_{max}	IGA + DNEH_GRASP + LS	ARPD	✓			Taguchi
[354]	2024		✓		C_{max}; TEC	MOIGA	IGD; HV; Δ	✓		✓	Taguchi
[355]	2024	✓			Labor cost + Electricity cost + Maintenance cost + Penalty cost	Improved TTA	Objective value		✓	✓	
[356]	2024	✓			$\sum w_j T_j$	Grouping GA + ILS	Heuristic performance	✓			Preliminary tests Literature
[357]	2024			✓	C_{max}; Machine *load*; $\sum\left(\alpha_j E_j + \beta_j T_j\right)$; Carbon emission	DGTOA	GD; IGD; HV	✓		✓	Taguchi
[358]	2024	✓			C_{max}	Improved Co-evolutionary MA	ARPD; Number of upper bound solutions reached		✓		Preliminary tests
[359]	2024	✓			$\sum C_j$	Adaptive IGA	RPD	✓			Full factorial DOE
[360]	2024	✓			$\sum T_j$	Population-based IGA	RDI	✓			Full factorial DOE
[361]	2024	✓			C_{max}	Shifting IGA	RPD	✓			Full factorial DOE
[362]	2024	✓			C_{max}	Adaptive ABC	RPD	✓			Full factorial DOE

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Table 3 (*continued*)

Paper ID	Year	Type of objective			Objective function (s)	Meta-heuristic algorithm (s)	Performance metric (s)	Test instances			Parameter optimization method
		Single-objective	Bi-objective	Multi-objective				RGTP	BP	RCA	
[363]	2024			✓	C_{max}; $\sum T_j$; TEC	Feedback-based ABC	SC; Metric ρ; DI_R	✓			Taguchi
[364]	2024		✓		C_{max}; TEC	NSGA-III	IGD; HV		✓	✓	Preliminary tests
[365]	2024			✓	C_{max}; *TEC*; Total starting time deviation	MDABC	GD; IGD; Δ	✓		✓	Taguchi
[366]	2024	✓			C_{max}	SFLA + Macro evolution + Local intensification + SA-based mechanism	RPD: Standard deviation	✓			Taguchi
[367]	2024		✓		C_{max}; TEC	Tree-based MOEA	IGD; SC; HV	✓			Taguchi
[368]	2024		✓		Average order waiting time; Average order delay rate	NSGA-II	IGD; HV		✓	✓	Preliminary tests
[369]	2024	✓			C_{max}	Variable-representation discerete ABC	RPD	✓			Full factorial DOE
[370]	2024	✓			C_{max}	Improved ABC	ARPD		✓		Taguchi
[371]	2024		✓		$\sum T_j$; TEC	MOMA	GD; IGD; Δ	✓			Taguchi
[372]	2024	✓			$\sum T_j$	Knowledge-based IGA	ARPD	✓			Taguchi
[373]	2024	✓			$C_1 AST + C_2 \sum E_j + C_3 \sum T_j$	Improved MA	RPD	✓			Preliminary tests
[374]	2024	✓			C_{max}	Extended collaborative VND	RPD	✓		✓	Iterated F-Race
[375]	2024		✓		C_{max}; TEC	Multi-group PSO-based MA	HV; IGD		✓		Full factorial DOE
[376]	2024	✓			$\sum w_j C_j$	Cooperative adaptive GA	RPD; Standard deviation	✓			Taguchi
[377]	2024		✓		C_{max}; TEC	Improved MA	SC; IGD; HV	✓			Taguchi
[378]	2024			✓	Total PC; Transportation cost; Operational utility	Two-stage MA	HV; IGD; Rnd metric	✓			Taguchi

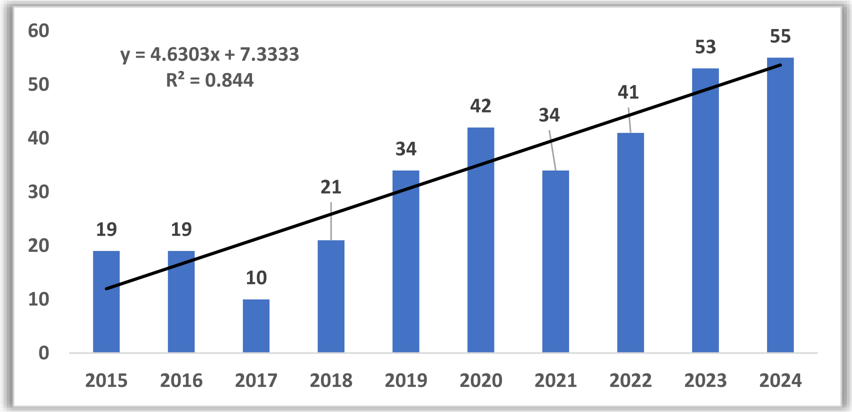

Fig. 3. Yearly distribution of the numbers of included articles.

Furthermore, there are 27 other countries such as Japan, Australia, Brazil, and Colombia except the top 10 where the authors contribute to this field. The total of 37 countries is distributed according to continents as Asia (16), Europe (10), Africa (3), North America (3), Australia (2), South America (2), and Asia-Europe (1). By the way, it is possible to infer that this research area is valid and common all around the world as a significant scheduling environment with a per-continent analysis.

The top 10 journals where the articles in which meta-heuristics are applied for solving HFSPs are published have been given in Fig. 5. 328 articles published in a total of 111 different journals have been examined in the scope of this analysis. These papers were mainly published in Computers & Industrial Engineering, Expert Systems with Applications, International Journal of Production Research, Applied Soft Computing, Swarm and Evolutionary Computation, IEEE Access, Computers & Operations Research, Journal of Cleaner Production, Mathematical Problems in Engineering, and Knowledge-Based Systems. 153 articles with a percentage of 47 are published in these journals. According to this analysis, it can be inferred that the probability of publishing an article in this research area is higher in these top 10 journals.

The percentage distribution of journals according to publishers has been given in Fig. 6. A total of 111 different journals in which the included 328 articles are published belong to 36 different publishers. The top five publishers are Elsevier (30 journals), Springer Nature (16 journals), IEEE (10 journals), MDPI (7 journals), and Taylor & Francis (6 journals), and 62 % of all journals belong to these top five publishers. The other publishers can be ensampled as Wiley, Emerald Group Publishing, Growing Science, Horizon Research Publishing, Inderscience, SAGE Publications, Tech Science Press, and Tsinghua University Press. It can be inferred that a new paper in this field has higher publication potential in the journals of Elsevier, Springer Nature, IEEE, MDPI, and Taylor & Francis.

The percentage distribution of the included articles according to type of objectives has been presented in Fig. 7 through a pie of pie chart. The included 328 articles have been mainly classified under three topics as single-objective (191 articles), bi-objective (99 articles), and multi-objective (more than two objectives) (38 articles). The bi-objective and multi-objective problems can be converted to single-objective form through normal or weighted sum of different objectives in order to solve them more easily. Therefore, the total 191 single-objective articles have been divided into three sub-groups as mono-objective (papers in which only one objective is optimized) (153 articles), normal sum of different objectives (12 articles), and weighted sum of different objectives (26 articles) with the percentages of 47, 4, and 8 respectively.

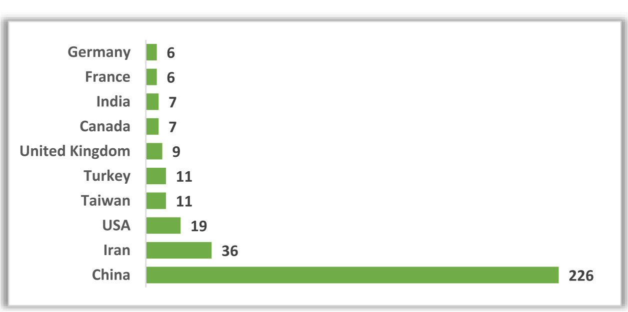

Fig. 4. The top 10 countries where meta-heuristics are applied for solving HFSPs.

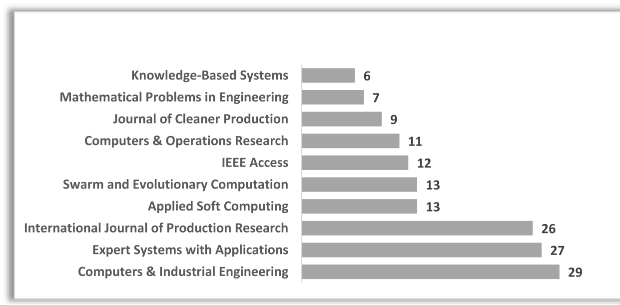

Fig. 5. The top 10 journals the articles in which meta-heuristics are applied for solving HFSPs are published.

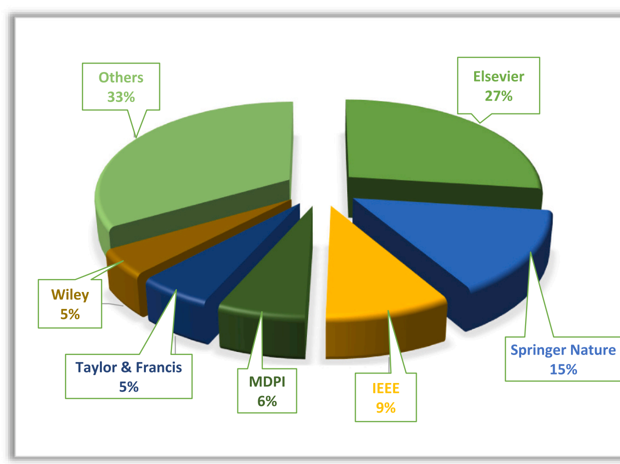

Fig. 6. Percentage distribution of journals according to publishers.

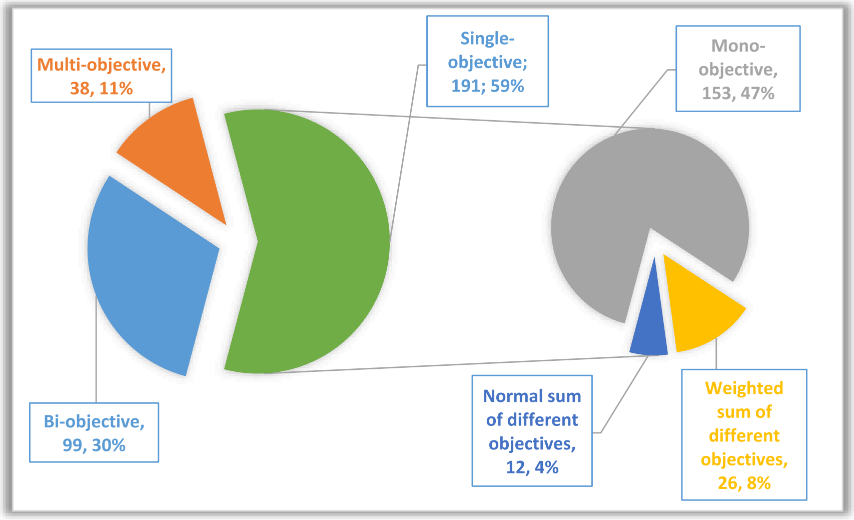

Fig. 7. Percentage distribution of included articles according to type of objectives.

Besides, bi-objective and multi-objective problems have percentage values of 30 and 11, respectively.

The most common objective functions aimed to be optimized in HFSPs have been presented in Fig. 8. Makespan, as a significant indicator of effective capacity utilization, is the most common objective function aimed to be optimized in HFSPs, either individually or together with other objective functions. Besides, total energy consumption, total tardiness, total weighted tardiness, and total energy consumption cost follow this objective function, respectively. In addition to the objective functions illustrated in Fig. 8, several other criteria have been considered for HFSPs, including mean completion time, inventory holding cost, maximum tardiness, number of tardy jobs, and mean flow time. It is possible to classify objective functions based on different characteristics such as completion time, due date, environmental sustainability, and cost. The objective functions except this classification, can be defined under the topic of others. Completion time based criteria ($C_{\max}$, $\sum C_j$, $\sum w_j C_j$), which aim to ensure efficient production, dominate the most common objective functions seen in Fig. 8 with a percentage of 56. Furthermore, the criteria related to environmental sustainability ($TEC, TECC, Total\ carbon\ emission$) and due date based criteria ($\sum T_j$, $\sum w_j T_j, \sum E_j, \sum w_j E_j$) aimed to provide punctuality and customer satisfaction follow these criteria respectively with percentages of 21 and 19. Due to the increasing importance of sustainable and cleaner production concepts, the use of environment-related criteria has also increased over the years. These criteria are generally optimized together with makespan as a completion time based criterion in bi-objective or multi-objective problems. While total PC is the most utilized cost-based criterion, $\sum W_j$ and AST can be evaluated under the topic of the others according to this classification.

The trendline related to the number of bi-objective and multi-objective articles according to years is given in Fig. 9. As seen in this figure, the R^2 value of the trendline has been obtained as 0.92, and this is quite reliable since it is close to 1. It can be inferred from this high value of R^2 that bi-objective and multi-objective articles related to HFSPs will grow rapidly in the next years. While the peak number has been reached in 2023 with 27 publications, it can be expected a new peak in the next years according to this trendline.

The top 15 meta-heuristic algorithms utilized for solving HFSPs have been given in Fig. 10. 90 different meta-heuristics have been applied in 328 included articles. As shown in this figure, GA (67 articles), SA (32 articles), NSGA-II (27 articles), PSO (27 articles), VNS (23 articles), ABC (23 articles), IGA (21 articles), MOEA (20 articles), MA (16 articles), and ACO (14 articles) are the top 10 most utilized meta-heuristics for solving HFSPs. These algorithms are followed by TS, DE, SFLA, EDA, and MBO, respectively. There are many different meta-heuristics, except presented in Fig. 10. and these algorithms can be ensampled as ICA, TLBO, VND, GRASP, GWO, ILS, NSGA-III, AIS, FA, and SPEA-II. There are at least 3 articles in which these algorithms are employed in order to solve HFSPs. It is certainly observed from Fig. 10 that while GA, SA, PSO, VNS, and ABC meta-heuristics are the top five algorithms for single-objective problems, NSGA-II and MOEA are the most used algorithms to solve bi-objective or multi-objective problems.

Hybrid meta-heuristics, which combine a meta-heuristic algorithm with another meta-heuristic, aim to make some improvements in terms of computational time and solution quality. The distribution of the number of hybrid meta-heuristics applied for solving HFSPs according to

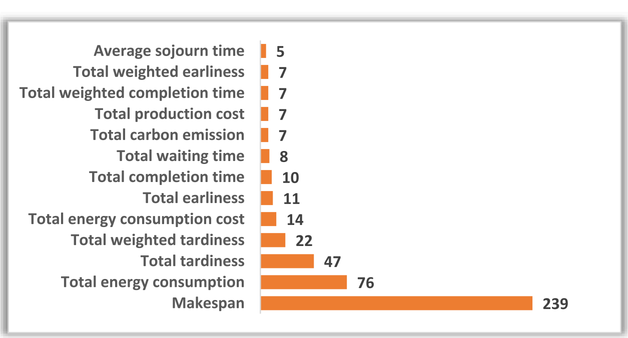

Fig. 8. The most common objective functions aimed to be optimized in HFSPs.

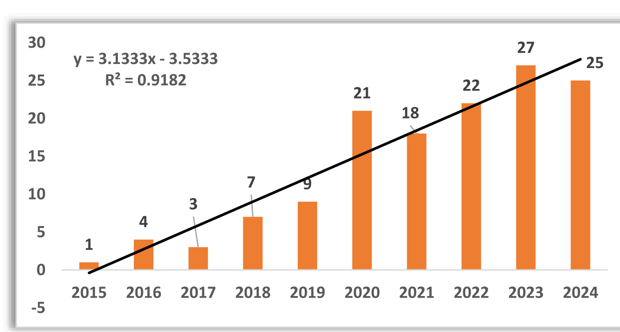

Fig. 9. Trendline related to the number of bi-objective and multi-objective articles according to years.

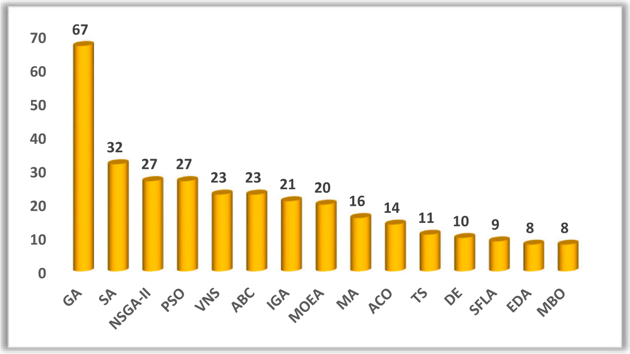

Fig. 10. The top 15 meta-heuristic algorithms utilized for solving HFSPs.

years has been presented in Fig. 11. While a total of 69 articles in which hybrid-meta-heuristics are utilized to solve HFSPs have been examined in the scope of statistical analysis during the review period, after the year 2018, there is a remarkable increase in the usage of these algorithms and the highest number of articles is seen in 2019, with the number of 12. According to this figure, it can be predicted that the utilization of hybrid meta-heuristics will increase over the years to solve any HFSP more efficiently in terms of computational effort and to obtain better solution quality.

Meta-heuristic algorithms can be classified according to different features such as the inspiration source and the number of solutions. In terms of the inspiration source, these algorithms can be divided into five groups as evolutionary algorithms, swarm-based algorithms, physics-based algorithms, human-based algorithms, and the others. Evolutionary algorithms are inspired by laws of biological evolution, such as natural selection, crossover, and mutation. Swarm intelligence based algorithms mimic the social and collective behaviors of animals such as birds, insects, fishes etc. Physics based algorithms simulate universal laws of physics such as electromagnetism, gravity, and momentum. Finally, human based algorithms are inspired by human social acts [41, 42]. The algorithms cannot be clearly assigned to this classification are classified under the topic of the others. The percentage distribution of meta-heuristic algorithms applied in the included articles according to the inspiration source has been presented in Fig. 12. As seen in this figure, evolutionary algorithms are the most utilized meta-heuristics to solve HFSPs, with a percentage of 42. Swarm-based, human-based, and physics-based algorithms follow them, with the percentages of 25, 15, and 8, respectively. While GA (67 articles), NSGA-II (27 articles), MOEA (20 articles), MA (16 articles), and DE (10 articles) are the most frequently employed evolutionary algorithms, PSO (27 articles), ABC (23 articles), ACO (14 articles), and MBO (8 articles) rank among the top 15 meta-heuristics as swarm based algorithms. Finally, VNS (23 articles) and SA (32 articles) are the most utilized human-based and physics-based algorithms, respectively.

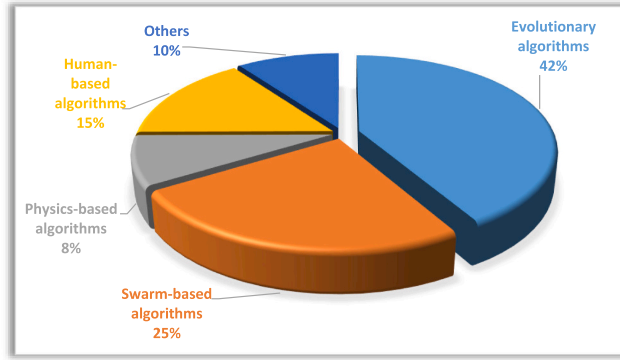

Fig. 12. A classification for meta-heuristic algorithms according to inspiration source.

The percentage distribution of meta-heuristic algorithms applied in the included articles according to the number of solutions has been presented in Fig. 13. Population-based algorithms are by far the most utilized to solve HFSPs, with a percentage of 81. While GA (67 articles), NSGA-II (27 articles), and PSO (27 articles) are the top three population-based algorithms, the most utilized single solution based algorithms can be given as SA (32 articles), VNS (23 articles), and TS (11 articles).

A wide range of performance metrics is utilized to evaluate the solution quality obtained through meta-heuristic algorithms for both single-objective and multi-objective HFSPs. A total of 18 different performance indicators were used in 191 single-objective articles examined in the scope of this review paper. The top 10 performance metrics utilized to evaluate solution quality in the single-objective HFSPs have been given with their usage counts in Fig. 14. As seen in this figure, RPD [2,351], calculated as percentage deviation from the best known value, is the most used performance indicator, with utilization in 95 articles, which are half of all the single-objective problems. ARPD [353,372] obtained by dividing RPD to the number of runs, deviation [241], RDI [344,360] which assists to measure distance between one solution and the local optimum solution in the solution space, SD [376] utilized to measure the stability of solutions obtained by any algorithm, HP [212, 356] a ratio of objective value of a meta-heuristic to the best objective value, EI [70,71], and RI [70,71] metrics follow this indicator. Furthermore, objective value obtained from any algorithm and computational time, which measures the running time of the algorithm to obtain optimal or near-optimal solutions, are also commonly utilized as performance metrics for assessment of algorithm performance and solution quality in the single-objective HFSPs.

A total of 55 different performance indicators were used in 137 bi-objective and multi-objective articles examined in the scope of this review paper. The top 15 performance metrics utilized to evaluate solution quality in the multi-objective HFSPs have been given with their usage

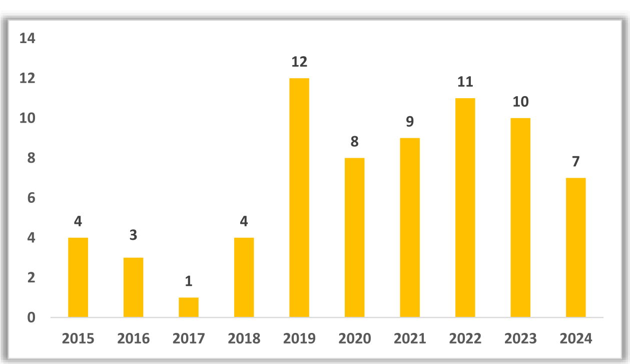

Fig. 11. Distribution of the number of hybrid meta-heuristics applied for solving HFSPs according to years.

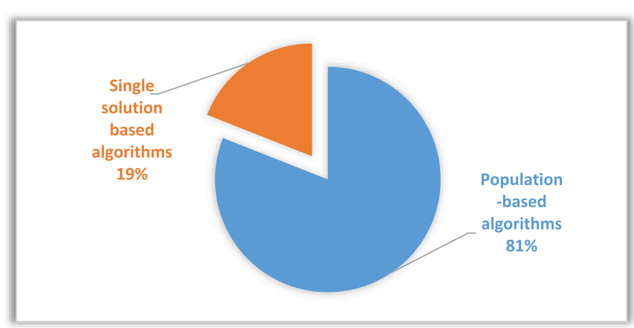

Fig. 13. A classification for meta-heuristic algorithms according to number of solutions.

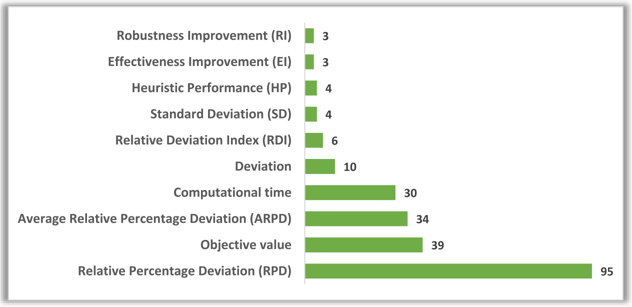

Fig. 14. The top 10 performance metrics utilized to evaluate solution quality in the single-objective HFSPs.

counts in Fig. 15. These indicators can be shortly explained according to usage counts in the descending order as follows [4,379]. IGD [303,350] is used to estimate the average distance from the reference front with best-known solutions to its closest solution. IGD with the weighted achievement scalar function is defined as metric DI_R [346,361] in some studies. Therefore, this metric has been evaluated as a synonym of IGD in this paper. SC [179,292] is utilized to measure the dominance relation between the Pareto solutions of two comparative algorithms. This metric is also defined as the Coverage metric (C-metric) in the literature. HV [286,297] is applied to measure the volume of the space between Pareto solutions obtained by the algorithm and the reference point. QM [4] is utilized to measure the percentage of solutions in the Pareto front that are part of the reference front with best-known solutions. The counts of Metric ρ [346], Rnd metric [378], metric Ω [243], and Percentage of Domination (POD) [13] have been added to the number of QM metric since these metrics are evaluated as synonyms of the QM metric. NNDS [60,276] indicates the number of non-dominated solutions obtained by each algorithm. The counts of Number of Pareto Solutions (NPS) and Overall Non-dominated Vector Generation (ONVG) metrics have been presented under the NNDS metric since they are the synonyms of this metric. GD [325,333] is used to represent the average distance between the obtained Pareto front and the reference front with best-known solutions. SM [100,304] contributes to compute the standard deviation of distances among Pareto solutions. Spread [180,333] is utilized to measure the diversity of non-dominated solutions. MID [8,245] is applied to measure the average distance from the Pareto front to the coordinate origin. Unary ε-metric [379] is calculated as the minimum distance that is required to transform the approximation set to dominate the reference set. DM [304] is applied to determine the extent of heterogeneity in the set of Pareto solutions for each algorithm. RAS [349] is utilized to measure the degree to the points in which Pareto-optimal solution set simultaneously reach the optimality of each objective. SNS [125] is used to indicate the measure of diversity of non-dominated solutions; in other words, it measures average deviation from MID. In addition, objective value and computational time are also utilized as performance indicators in the multi-objective problems, fewer than single-objective problems.

Three types of test instances, as randomly generated test problems, benchmark problems, and real case applications, are utilized in experimental analyses to evaluate the efficiency and applicability of the proposed meta-heuristic algorithms. If there is no benchmark problem in the literature due to the novelty of the handled problem in terms of machine environment, constraints, and objective functions, randomly generated test problems are formed to evaluate the performance of the proposed meta-heuristic algorithms. Sometimes, benchmark instances existing in the literature are utilized for performance assessment of the algorithms. Real case applications, including a problem related to a real-life scheduling environment, can also be utilized for this aim. The percentage distribution of test instances utilized for performance evaluation of meta-heuristics in the included articles has been presented in Fig. 16. Randomly generated test problems are the most used test instances to evaluate the efficiency and applicability of the meta-heuristics, with a percentage of 70. Real-case applications and benchmark problems follow these types of test instances, with percentages of 17 and 13, respectively.

The performance of meta-heuristic algorithms and the solution quality obtained using these algorithms are strongly dependent on the

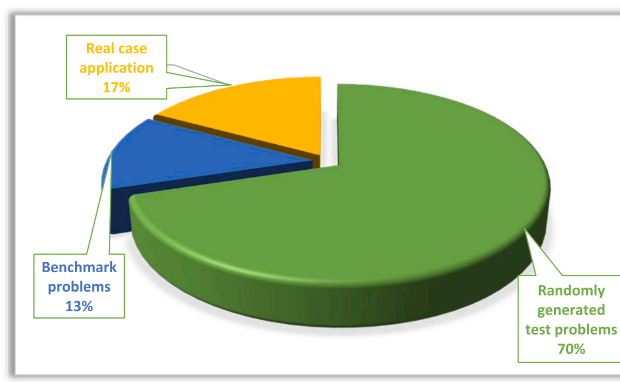

Fig. 16. Percentage distribution of test instances utilized for performance evaluation of meta-heuristics.

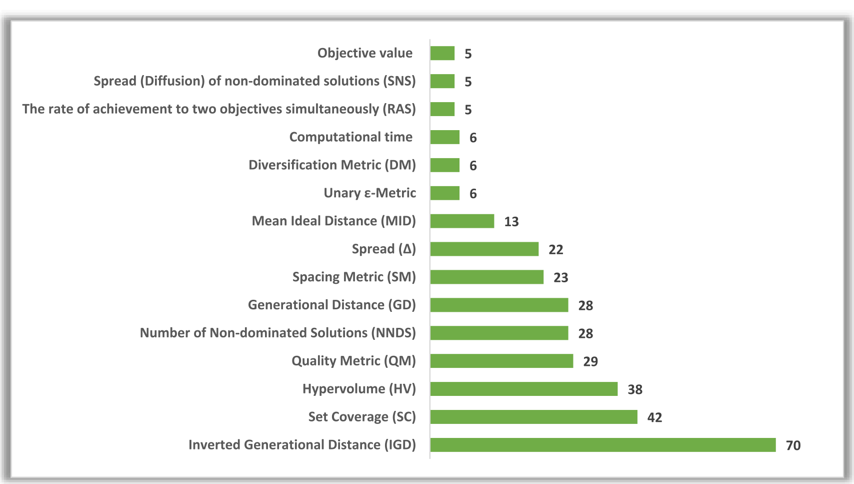

Fig. 15. The top 15 performance metrics utilized to evaluate solution quality in the multi-objective HFSPs.

determination of the most appropriate parameter values. For this aim, different parameter optimization methods are utilized in studies in which meta-heuristic algorithms are applied for solving HFSPs. The percentage distribution of methods utilized for parameter optimization of meta-heuristics in the included articles has been presented in Fig. 17. As seen in this figure, the Taguchi design of experiment (DOE) method is the top technique utilized for parameter optimization in articles, in which a parameter optimization method is utilized with a percentage of 47. It can be stated that the Taguchi method is the most frequently preferred approach, as it reduces computational effort by avoiding the need to test all possible experimental combinations. This method is followed by preliminary tests, full factorial DOE, and literature review with the percentages of 25, 18, and 6, respectively. The other methods presented by 4% include different techniques such as response surface methodology, experience, artificial neural networks, automated algorithm design, chess rating system, fuzzy logic control, irace package, iterated F-race, and orthogonal experiment.

5. Conclusions and future research suggestions

In this paper, a comprehensive and systematic literature review related to meta-heuristic algorithms applied for solving HFSPs for a decade from 2015 to 2024 has been conducted. For this aim, PRISMA methodology, which enables the realization of systematic reviews and meta-analyses in a specified research area, has been executed in the scope of this study. As a result of performing this systematic review methodology, a total of 328 articles have been determined, and these articles have been analyzed in terms of many different features such as year, country, journal, publisher, objective functions, meta-heuristic algorithms, performance metrics, test instances, and parameter calibration techniques. The results of these statistical analyses have been presented via pie and bar charts in Section 4. Thus, it has been aimed to demonstrate the recent advances in this research topic, which has gained significant attention over the years by responding to 12 predetermined research questions and to provide a beneficial road map for various stakeholders, consisting of academic researchers, experts, and industrial managers.

To the best of the authors' knowledge, this is the first review paper that is devoted to examining meta-heuristic algorithms applied for solving HFSPs in the existing literature. This exhaustive review study has been conducted to add leading analyses related to the utilization of meta-heuristics to solve this type of scheduling problem to the literature. Firstly, as a result of these analyses, it has been seen that the number of articles has increased over the years with a meaningful trend, and these articles are published in a total of 37 different countries, which are from all continents of the world. It can be inferred that this is a promising research area for the coming studies by the way of suggesting new meta-heuristic optimization algorithms with their exceptional ability to handle combinatorial optimization problems for solving HFSP, since this problem has an NP-hard structure. At this point, we can say that the utilization of meta-heuristics for HFSPs will grow at high speed, and contemporary methods will be proposed over the time horizon. Many new articles are published every year that aim to obtain high quality solutions using meta-heuristic algorithms for solving HFSPs. We believe that this review paper helps researchers and practitioners in obtaining detailed information about meta-heuristic optimization algorithms utilized for solving HFSPs and suggesting efficient meta-heuristics for this type of scheduling problem.

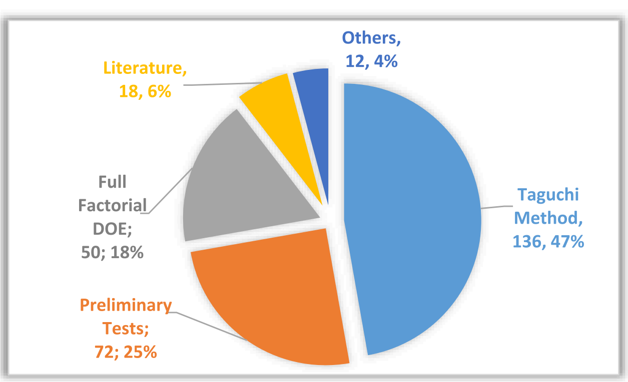

Fig. 17. Percentage distribution of methods utilized for parameter optimization of meta-heuristics.

The results obtained from meta-analyses show that evolutionary and swarm-based algorithms are the most utilized methods for solving HFSPs, with a total percentage of 67 when a classification is made according to the inspiration source of meta-heuristic algorithms. In this context, it is observed that GA (67 articles) and PSO (27 articles) are the most applied evolutionary and swarm-based algorithms, respectively, and they are also located in the top five meta-heuristics in terms of utilization for HFSPs. It is possible to say that this state is caused by the first usage date of these algorithms and their simplicity to understand and to implement in terms of the inspiration source and mathematical framework. While NSGA-II, MOEA, MA, DE, SFLA, and EDA are the other most utilized evolutionary algorithms, ABC, ACO, and MBO can also be given as examples of the most popular swarm-based algorithms. Furthermore, human-based and physics-based algorithms have a total ratio of approximately one-fourth, and VNS (23 articles) and SA (32 articles) are the most applied human-based and physics-based algorithms, respectively. On the other hand, when a classification is made in terms of the number of solutions, population and single solution-based algorithms have percentages of 81 and 19, respectively. It is seen that the high utilization of GA, NSGA-II, PSO, ABC, and MOEA highlights the population-based algorithms. SA, VNS, and TS are the most utilized single solution-based algorithms. Besides, VND, GRASP, and ILS can be given as examples of less frequent single solution-based algorithms.

Various performance metrics are used to evaluate the performance of the proposed meta-heuristics for both single-objective and multi-objective HFSPs. A total of 18 different performance metrics are observed by analysing the 191 included single-objective articles. RPD, computed as a percentage deviation from the best objective value, is the most utilized performance indicator for performance assessment of the proposed algorithms in the single-objective problems, with utilization in 50 % of the 191 articles. Furthermore, a total of 55 different performance metrics are observed by analysing the 137 included multi-objective articles. IGD, SC, HV, QM, and NNDS are the top five performance indicators used for performance evaluation of the developed meta-heuristics in the multi-objective problems. On the other hand, experimental analyses are carried out for the evaluation of the efficiency and applicability of the proposed meta-heuristic algorithms using three types of test instances as randomly generated test instances, benchmark instances, and real-life cases. Since the HFSPs examined in the scope of the included articles generally have their specific constraints and processing characteristics and objectives, randomly generated test instances are utilized with a percentage of 70 for performance assessment of the proposed meta-heuristic algorithms. Real case applications are located in the second order, with a percentage of 17 due to various applications of HFSPs in different industries such as metal, electronic, automotive, glass, and furniture. Some HFSPs are utilized as benchmark instances to evaluate the performance of meta-heuristics, with a percentage of 13 in the included articles. Finally, since the determination of the most suitable parameter levels strongly affects the solution quality obtained from the meta-heuristic algorithms, a descriptive statistical analysis has been conducted devoted to parameter optimization techniques in the scope of this review paper. The Taguchi method is the most employed parameter optimization method, with a percentage of 47, because of providing a crucial advantage in terms of computational effort by decreasing the number of experiments through the utilization of orthogonal arrays. Preliminary tests, full factorial DOE, and the parameter levels obtained from the literature review follow this method, respectively.

The utilization of meta-heuristics together with machine learning (ML) techniques has gained increasing attention in the scientific literature in recent years and researchers prefer this approach to improve the search performance of the applied meta-heuristic optimization algorithms and to obtain high-quality solutions. In this context, reinforcement learning (RL) has attracted significant attention as an aspect of ML and some methods of RL such as Q-learning and State-Action-Reward-State-Action (SARSA) algorithms are utilized to solve different scheduling problems. The idea of embedding an RL technique into the algorithmic framework, which provides to improve the search performance for better solutions, is effectively applied in the studies that utilize meta-heuristic algorithms for solving HFSPs. It is observed that RL-based meta-heuristics are more advantageous compared with traditional meta-heuristics, with autonomous decision-making ability and avoiding heavy calibration of search operators. Even though the types of problems and their scales are different, it may be possible to immediately apply RL-based meta-heuristics to the new scheduling problems by adjusting the search operators. Q-learning, a famous model-free RL algorithm, is commonly utilized together with meta-heuristic algorithms applied for solving HFSPs to determine dynamically an action in a state and to choose operators intelligently. In this algorithm, the agents interact with the environment, and continuous updates occur in their states. Following the execution of each selected action, these agents receive a reward or penalty. On the other hand, RL techniques can be applied in the scope of parameter calibration, which helps to determine the most appropriate parameter set, in other words, to select the key parameters automatically in the studies in which meta-heuristic optimization algorithms are utilized. In addition, ML methods may contribute significantly to the generation of high-quality initial solutions for meta-heuristic algorithms. The meta-heuristic algorithm starts search from a more advantageous point in the solution space and can both increase the convergence speed and the probability of obtaining better solutions in this way.

As a result of this review study, it is certainly possible to say that the HFSP will remain as a significant research area in the future due to the practical relevance of this problem. In this context, the following points can be defined as future research suggestions by taking into consideration the outputs of this review.

- From a methodological point of view, initially, the utilization of new generation meta-heuristic algorithms to solve HFSPs and to compare their performance with the existing and mostly utilized algorithms can be suggested as a future research suggestion. Moreover, due to the importance of the elements related to meta-heuristics such as operators and neighborhood structures, it can be proposed to develop problem-specific operators instead of standard operators that are widely utilized, which provide to comprehensively handle the properties of the studied problem and to obtain better solutions. On the other hand, hybrid meta-heuristics combining two or more meta-heuristic algorithms can also be efficient options for solving HFSPs in the coming years, and in this direction, it can be expected to increase the number of publications including a hybrid meta-heuristic to reach better results for HFSPs in the future. Finally, the utilization of constructive heuristics to obtain promising initial solutions can improve the performance of the meta-heuristic algorithms and the quality of solutions. In this context, it can be proposed to develop problem-specific constructive algorithms and to evaluate their performances.
- It can be expected to significantly increase the utilization of ML-based approaches for improving the performance of the solution algorithm through adaptively selecting operators for solving HFSPs in future studies. Even though there are limited papers published in recent years in which ML methods are applied to solve this type of scheduling problems in the existing literature, the integration of RL with meta-heuristic algorithms reveals significant potential for improving solution quality and accelerating search ability. In this context, we anticipate performing RL together with new meta-heuristic algorithms to solve different versions of HFSPs including various problem-specific constraints and objective functions. In addition, it can be suggested to solve multi-objective HFSPs with RL-based meta-heuristics as an essential future research direction.
- It is obviously observed that energy-efficient HFSP has gained significant attention in recent years owing to the increasing importance of the green production concept. At this point, the most commonly utilized environment-related criteria are TEC and TECC in this type of scheduling problem. However, the other environment-related criteria such as total carbon emission, total carbon footprint, green production indicator, total material wastage, and noise pollution are rarely used in multi-objective HFSPs. Since these criteria are crucial for reducing environmental damage rooted in industrial manufacturing, it can be suggested to handle them more in multi-objective problems as a future research suggestion.

The compilation of articles in the review process depends on the chosen databases and the keywords employed in the database searching. At this point, there is a possible risk of overlooking relevant articles because of the limitations of the selected databases and the insufficiency of the keywords utilized for database searching. Therefore, in the identification phase, we aimed to carry out a strict review process by conducting a search in five different academic databases and using six divergent keywords, and to prevent the effect of this limitation. In addition, meta-heuristic algorithms are indispensable in solving HFSPs in terms of computational efficiency which indicates producing high-quality solutions in an acceptable time, flexibility which states the advantage of modelling the addressed problem under complicated constraints, and solution quality with the ability of escaping from local optimum and integrating with local search and problem-specific heuristics. However, significant limitations related to the utilization of the meta-heuristic algorithms for solving HFSPs are indicated as follows. (i) The performance of the meta-heuristic algorithms is highly dependent on parameter selection, and it is still an exact problem that generalizes the determination of these parameters. (ii) An algorithm that performs successfully for certain HFSP variants may not perform the same under different problem sizes or constraints. (iii) Meta-heuristics are mostly evaluated empirically and do not ensure convergence or optimality. (iv) Meta-heuristic algorithms are unable to adapt quickly enough to dynamic events such as machine failure, new job arrival, and job cancellation. These shortcomings necessitate to the development of adaptive, learning-based, and hybrid approaches in the future.

On the other hand, according to the results of this review study, it is clearly seen that meta-heuristic algorithms are applicable in real-life multi-stage production environments including practical constraints like sequence-dependent setup times, limited buffer, machine eligibility, and precedence constraints among jobs such as automotive, electronic, chemical, metal, and glass industries. Besides, the adaptability of the meta-heuristics as the problem size and the structure of the manufacturing system change increases their applicability in different industries. These algorithms can also contribute to real-time and short-term production planning by producing high-quality near-optimal solutions within a reasonable time instead of optimal solutions. It can be possible to integrate meta-heuristic optimization algorithms into industrial applications with relatively low software development costs, without the need for complex mathematical solvers. Therefore, we can say that the meta-heuristics reveal not only theoretical insights but also practical managerial implications for production scheduling. Finally, we can say that the classification table given in Section 3 and the statistical analysis results presented in Section 4 can be very beneficial for academic researchers, experts, and industrial managers studying on both meta-heuristic optimization algorithms and HFSPs.

CRediT authorship contribution statement

Murat Çolak: Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Gülşen Aydın Keskin:** Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization.

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.

Appendix A

The acronyms of the algorithms located in Table 3 is presented in this Appendix.

Table A.1
Acronyms of algorithms existing in Section 3

Acronym	Expansion
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AIS	Artificial Immune System
AO	Aquila Optimizer
AOA	Archimedes Optimization Algorithm
ASMOAP	Adaptive Selection Multi-objective Optimization Algorithm with Preference
ATCM	Adaptive Tent Chaos Mapping
BBO	Biogeography Based Optimization
BSO	Brain Storm Optimization
CBMA	Collaboration-based Multi-objective Algorithm
CCABC	Cooperative Co-evolutionary Artificial Bee Colony
CCEA	Cooperative Coevolutionary Algorithm
CDS	Campbell, Dudek, and Smith
CH	Constructive Heuristic
CS	Cuckoo Search
DE	Differential Evolution
DGSK	Dimension-aware Gain-sharing Knowledge
DGTOA	Discrete Group Teaching Optimization Algorithm
EA	Evolutionary Algorithm
EDA	Estimation of Distribution Algorithm
EHO	Elephant Herding Optimization
EMA	Electromagnetism-like Algorithm
FA	Firefly Algorithm
FFO	Fruit Fly Optimization
GA	Genetic Algorithm
GP	Genetic Programming
GRASP	Greedy Randomized Adaptive Search Procedure
GS	Gravitational Search
GWO	Grey Wolf Optimizer
HNN	Hopfield Neural Network
HPAEA	Hyperplane Assisted Evolutionary Algorithm
HS	Harmony Search
IA	Immune Algorithm
IBLS	Iterative Backward List Scheduling
ICA	Imperialist Competitive Algorithm
IGA	Iterated Greedy Algorithm
ILS	Iterated Local Search
KMOEA	Knowledge-based Multi-objective Evolutionary Algorithm
LS	Local Search
MA	Memetic Algorithm
MBO	Migrating Birds Optimization
MDABC	Multi-objective Discrete Artificial Bee Colony
MFOA	Moth Flame Optimization Algorithm
MMBO/D	Multi-objective Migrating Bird Optimization Based on Decomposition
MOABC	Multi-objective Artificial Bee Colony
MOABC/D	Multi-objective Artificial Bee Colony based on Decomposition
MOALO	Multi-objective Ant Lion Optimization
MOEA	Multiobjective Evolutionary Algorithm
MOEA/D	Multiobjective Evolutionary Algorithm Based on Decomposition
MOEA/IOD	Multi-objective Evolutionary Algorithm Based on Inverse Optimization and Decomposition
MOEES	Multi-objective Energy-efficiency Scheduling
MOFA	Multi-objective Firefly Algorithm
MOGA	Multi-objective Genetic Algorithm
MOHHO	Multi-objective Harris Hawks Optimizer
MOHIG	Multi-objective Hybrid Iterated Greedy
MOHS	Multi-objective Harmony Search
MOICA	Multi-objective Imperialist Competitive Algorithm
MOIGA	Multi-objective Iterated Greedy Algorithm
MOIWO	Multi-objective Invasive Weed Optimization

(*continued on next page*)

Table A.1 (*continued*)

Acronym	Expansion
MOMA	Multi-objective Memetic Algorithm
MOMBO	Multi-objective Migrating Birds Optimization
MOMVO	Multi-Objective Multi-Verse Optimizer
MOPSO	Multiobjective Particle Swarm Optimization
MOROA	Multi-objective Rider Optimization Algorithm
MOSA	Multi-objective Simulated Annealing
MOTLBO	Multi-objective Teaching-learning Based Optimization
MOVNS	Multi-objective Variable Neighborhood Search
MOWOA	Multi-objective Whale Optimization Algorithm
MRLM	Meta-reinforcement Learning-based Metaheuristic
MVO	Multi-verse Optimizer
NEH	Nawaz, Enscore and Ham
NEMAS	Nash Equilibrium Machine Assigment Scheme
NRGA	Non-dominated Ranking Genetic Algorithm
NS	Neighborhood Search
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NSGA-III	Non-dominated Sorting Genetic Algorithm III
OCBA	Optimal Computing Budget Allocation
PESA-II	Pareto Envelope-Based Selection-II
PIOA	Pigeon-Inspired Optimization Algorithm
PSO	Particle Swarm Optimization
RKGA	Random Key Genetic Algorithm
SA	Simulated Annealing
SFLA	Shuffled Frog Leaping Algorithm
SMO	Spider Monkey Optimization
SPEA-II	Strength Pareto Evolutionary Algorithm II
SPT	Shortest Processing Time
SSA	Salp Swarm Algorithm
TLBO	Teaching Learning Based Optimization
TMOA/D	Three-stage Multi-objective Approach Based on Decomposition
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TS	Tabu Search
TSCNSA	Two-stage Cross-neighborhood Search Algorithm
TTA	Tiki Taka Algorithm
VBIH	Variable Block Insertion Heuristic
VND	Variable Neighborhood Descent
VNDS	Variable Neighborhood Decomposition Search
VNS	Variable Neighborhood Search
WOA	Whale Optimization Algorithm
WSA	Whale Swarm Algorithm
WWOA	Water Wave Optimization Algorithm

Data availability

Data will be made available on request.

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